# Assessing and communicating climate change uncertainties

*- Case of the Rhine basin -*

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# Contents

# Chapter 1

## Introduction

## 1.1 The complexity of climate change uncertainties

The Rhine river basin is the fourth largest basin in Europe and the busiest waterway for inland navigation in Europe (Middelkoop et al., 2004). It is densely populated, with approximately 50 million inhabitants and includes highly industrialized areas. The largest parts of the basin are located in Germany and the Netherlands. Both countries have high safety standards and the Netherlands even has one of the highest safety levels for water management in the world. The dikes in the most populated areas are built to withstand a flood with a return period of 10,000 years. Studies show that climate change could have an impact on the Rhine discharge regime, and thereby on flood risk (Hooijer, Klijn, Pedroli, & Van Os, 2004; Middelkoop et al., 2001; Te Linde, Aerts, Bakker, & Kwadijk, 2010; Te Linde, Bubeck, Dekkers, De Moel, & Aerts, 2011). The return periods of a flood of 10,000 years could be largely reduced and given the high density of population and high value of capital in this area, the impact of a major flood could be devastating.

The question is what we know about changes in future flood risk. To assess changes in flood risk, often a chain of models is used. First, climate models make projections for changes in the future. The models are driven by socio-economic as well as greenhouse gas emission scenarios and produce global projections for changes in variables like temperature and precipitation. The global projections are downscaled to smaller scales because people experience the impact of climate change on a local scale. To assess and quantify changes in future flood risk the local projections of changes in temperature and precipitation are used as input to an (hydrological) impact model. Depending on the severity and timing of the projected changes in flood risk, a decision maker will decide whether and when it is necessary to implement measures and if they need to be drastic or not.

The story above describes a straight forward process to deal with climate change. It belongs to the rationalist-instrumental model of communication in which scientific research helps to discover an environmental problem, identifies options for the problem's potential solution and scientists inform politicians of these findings (Weingart, Engels, & Pansegrau, 2000). This linear conceptualisation of the relation between science and policy (Huitema & Turnhout, 2009) fits well with our current society which has a strong emphasis on science- and evidence based policy making (Sanderson, 2002). Science- and evidence based policy making, however, has encountered some problems in the field of climate change. One of the main problems is that the projections of climate change are subject to large uncertainties. This makes it impossible for scientists to convey a clear message about the direction and extent of climate change. For example, the severity and timing of climate change impacts are uncertain and even the climate change impact itself is sometimes uncertain. Furthermore, climate science is very complex, which makes it difficult for a scientist to explain the origin and value of uncertainties. Part of the projected climate changes are, for example, embedded in natural climate variability. Therefore, the detection of the human contribution of climate change is not always clear (Hegerl & Zwiers, 2011). If decision makers intend to develop adaptation strategies that aim to manage the impacts of human induced change, it is important that they are able to make the distinction between natural climate variability and human induced change (Dupuis & Biesbroek, 2013). However, the combination of complexity and uncertainty of climate science makes it complicated for the decision maker to utilize the climate projections into robust adaptation strategies.

Finding ways to address the complexity of climate change uncertainties and creating frameworks that allow the uncertainties to aid instead of hinder decision making is currently one of the main scientific challenges in the climate change research community. Therefore, the principal aim of this thesis is to analyse the climate change uncertainties that are important to take into account for long term water management and to explore the communication of these uncertainties. This thesis addresses this aim using the Rhine basin as a case study area.

## 1.2 Characterizing and quantifying uncertainties

Advances in science and observations of climate change increase our understanding of the variability of the earth system and the responses to human and natural influences. The impact of climate change to the environment does not solely depend on the response of the earth system to changes in radiative forcings, but also on the response of society, such as changes in economy and technology, and the development of mitigation and adaptation policies (Moss et al., 2010). Projections of climate change are characterized by large uncertainties, which accumulate through the modelling chain, from socio-economic scenarios to local impacts, as shown in Figure 1.1.

Following Dessai and Hulme (2004) the 'nature' of uncertainty can be defined by three types:

1. Epistemic uncertainty
2. Stochastic uncertainty
3. Human reflexive uncertainty

Epistemic or systematic uncertainty originates from incomplete knowledge of the natural and social processes determining climate change, which can also be classified as system uncertainty. This type of uncertainty includes unknown values for the climate sensitivity, unknown rates of carbon uptake and parameter and structural uncertainty. An estimation of epistemic uncertainty can be made by assessing the outputs of different climate models. Stochastic uncertainty concerns the nonlinear behaviour of the climate system, randomness and initial conditions uncertainty. By using an initial conditions climate model ensemble, which is made by creating small variations in the start-up conditions of a climate model, an estimation can be obtained for the stochastic uncertainty. Stochastic uncertainty can also be viewed as natural climate variability. The third type of uncertainty is introduced by the social system. Humans can reflect critically on information regarding their behaviour. Society is likely to act when scientists agree that the climate is changing. In addition, observations of impacts of climate change can trigger human action. It can result, for example, in policy response through mitigation strategies. The behaviour of society influences the projections of socio-economic developments. This type of uncertainty is known as human reflexive uncertainty. An estimation of human reflexive uncertainty can be obtained by comparing different policy scenarios.

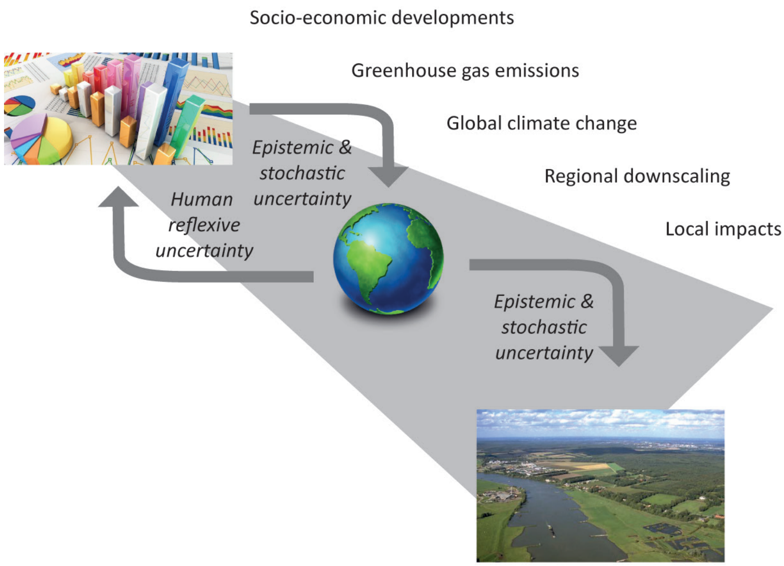


**Figure 1.1.** Cascade of uncertainties in climate change projections, from socio-economic developments to local impacts.

Figure 1.1 depicts that each step of the modelling chain includes uncertainty. The uncertainty accumulates with the sequence of steps, which has been described conceptually by Schneider (1983) as 'cascading pyramid of uncertainties', a construct that has been developed further by later authors (e.g. Giorgi, 2005; Mearns et al., 2001; New & Hulme, 2000; Stainforth, Downing, Washington, Lopez, & New, 2007; Wilby & Dessai, 2010). Each step of the modelling chain is subject to different uncertainties, which belong to the main classification scheme of Dessai and Hulme (2004). The climate model steps and associated uncertainties are described below:

*Socio- economic and emission scenarios*
Scenarios are plausible descriptions of how the future might unfold. Socio-economic scenarios describe how world population, economies, political structures and lifestyle

may evolve over the 21st century. These socio-economic scenarios are translated into greenhouse gas emission scenarios. The changes in emission concentrations can then be used as input for global climate models. The latest IPCC (Intergovernmental Panel on Climate Change) scenarios (Moss, et al., 2010) are developed in a parallel process, meaning that the emission scenarios, representative concentration pathways (RCPs), are used as input to climate models. In addition, a mixture of future impacts, vulnerabilities, adaptation and mitigation challenges was developed, called shared socioeconomic pathways (Kriegler et al., 2010). To develop socio-economic and emission scenarios, many assumptions have to be made. For example, about economic or population growth and technological developments. This makes projections of future socio-economic conditions uncertain and they become increasingly uncertain into the future (Arnell et al., 2004). These uncertainties cannot be adequately depicted in terms of chances of probabilities (Dessai & Van der Sluis, 2007); the scenarios rather describe a range of possible future's.

*Climate models*

The dynamics of the climate system are determined by a set of highly linked and tightly interacting physical processes. Climate models are designed to simulate the physical processes of the earth system. Future projections of the climate can be generated by these models as they are able to give a physics-based response to increased $CO_2$ concentrations and changes in other forcings. Although climate models have steadily become more robust over the past decades, they have also become more complex and the uncertainty for projections of precipitation and discharge is high (Maslin & Austin, 2012). This is mainly due to uncertain parameterizations and new modules that are added in each climate model generation, which increase the complexity of processes and feedbacks (e.g. chemical atmospheric interactions). The unresolved processes also include feedbacks and processes we are not aware of. Part of this uncertainty can be described by a multi-model ensemble (Taylor, Stouffer, & Meehl, 2012). A multi-model ensemble consists of different climate models, with each their own parameterization and physics. The projections differ for each model and thereby give a measure for the model uncertainty. Next to the model uncertainties described above, the outputs of the models on short time scales are also sensitive to the value of the observations used to initialize the model. One model run describes one realization of a possible climate, just as the climate we have observed until now can be seen as one realization. If variations are made in initial conditions of a climate model, an initial condition ensemble can be created, which gives a measure for natural climate variability. Natural climate variability, or internal climate variability, occurs in the simulated model system, but is also part of the 'real' climate system. Natural climate variability stems from the inherently unpredictable nature of climate fluctuations. An example of a natural source of variability is the North Atlantic Oscillation, which can cause climate extremes such as, the unusual cold and snowy winter in North-Western Europe of 2009-2010 (Cattiaux et al., 2010).

*Regional Downscaling*
Global climate models (GCMs) are used to assess climate change. However, their resolution is rather coarse and less suitable for analysing local impacts. Moreover, they cannot resolve significant local scale features, such as topography, land use and clouds. To address this problem, downscaling techniques have been developed. The techniques can be divided in three main approaches. The first approach is called dynamical downscaling, where a regional climate model (RCM) is nested within a GCM. The GCM provides the boundary conditions for the RCM. The second approach uses statistical methods to establish a relationship between the low resolution output of the GCM and the local climate. The third approach uses 'change factors', also known as the delta change method, which allows for a rapid impact assessment. For an extensive overview of the approaches see Fowler et al. (2007).

The RCMs often provide a more realistic presentation of key physical processes than the GCMs, but they have also model uncertainty. Similar to dynamical downscaling, statistical downscaling is dependent on GCM boundary forcing. Furthermore, the statistical methods depend on assumptions, like the stationarity of the predictor-predictand relationship in time, which causes uncertainty. Also, the statistical methods are dependent on the accuracy and geographical distribution of the observations which are used to calibrate the relationships (Maraun et al., 2010). The delta change method is subject to many of the same uncertainties as the statistical downscaling approaches. It has no predictor-predictand relationship, but assumes a stationary temporal structure (Diaz-Nieto & Wilby, 2005).

*Impact models*
Impact models are used to assess the impact of climate change on biological and societal systems such as, the food production (Biemans et al.), electricity supply (Van Vliet et al., 2012), or crop growth (Supit et al., 2012). The primary sources of uncertainty of impact models stem from measurement errors, variability and model structure (Morgan & Henrion, 1990). For the analysis of changes in discharge and flood risk, hydrological models are used. Hydrological modelling represents the physical process of runoff production through mathematical formulations. Two main uncertainties of hydrological modelling are derived from measurements and structural uncertainty of the model (Prudhomme, Jakob, & Svensson, 2003). The measurement uncertainty is related to the measurements that are used to calibrate and validate the model. The structural uncertainty stems from the algorithms that are used to describe the hydrological process and parameter and scaling uncertainty, which stems from scaling in both space and time.

Depending on the location, time scale and variable of interest, the different sources of uncertainty are more or less important for changes in river discharge. Although the results of studies are often difficult to compare due to the differences in research aim and design, overall it has been shown that the three largest sources of modelling uncertainty introduced for mid (2050) or long term (2100) water management (river basin or catchment level) are in decreasing order (Chen, Brissette, Poulin, & Leconte, 2011; Dobler, Hagemann, Wilby, & Stötter, 2012; Kay, Davies, Bell, & Jones, 2009; Liebert et al., 2012; Prudhomme & Davies, 2009; Velázquez et al., 2013):

1. Global climate response, which is expressed by GCM uncertainty
2. Regional climate response, due to downscaling techniques
3. Local water response (impact), uncertainty part of the hydrological modelling



## 1.3 Approaches to dealing with climate change uncertainties

Different frameworks have been developed to assess the different types of climate change uncertainties and to make them useful for decision making. Two main approaches can be identified to assess the uncertainties, namely top-down and bottom up (Dessai & Hulme, 2004). Top-down approaches, also known as 'predict-then-act' or 'scenario-led', start with global projections of future climate change. The global projections are followed by a linear step-wise procedure in which they are downscaled to local levels and used in local impact models. Historically, this is the dominant approach used, for example, in the early guidelines of the IPCC (Carter, Parry, Harasawa, & Nishioka, 1994) and the approach is still the most common (Pielke Sr et al., 2012; Wilby & Dessai, 2010). The top-down approach aims for the optimum strategy based on the best available knowledge. A substantial criticism is that it relies heavily on the foundations of the climate models and on their ability to make reliable projections for the future. Bottom-up approaches start with the assessment of the current system of interest, sensitivity to current weather and climate is analysed and then traced backwards along the risk pathway. The approach focuses also on the existing capacity of the social system to deal with climate hazards, by e.g. semi-structured interviews, participant observation, focus groups and published and un-published literature (Johnson & Weaver, 2009). The weakness of the bottom-up approach is that it is less capable of dealing with changes outside the range of experience. In addition, the complexity of the approach can be a weakness, making it time and resource intensive. An example of a bottom-up approach is to add a safety margin on top of the design flood level, to account for uncertainties or events that are not foreseen or have occurred yet (see for further details Dessai and van der Sluis (2007)). It is also possible to combine the top-down and bottom-up approaches. In combined approaches the output of a top-down approach is used to assess the vulnerability of a system to future changes. An example of this is the robust decision making approach (Lempert, Groves, Popper, & Bankes, 2006) or the adaptation tipping point approach (Kwadijk et al., 2010) .

The representation of uncertainties within either the top-down or bottom-up approach is currently topic of an international scientific debate. One main motivation for quantifying uncertainty of climate change impacts is its use in risk assessments.

Risk assessments can guide a policy maker in the reduction of risk, which is defined as the likelihood of an event times its consequence. A risk assessment can be based on two types of projections. The first type is deterministic with specific estimates of what will happen. The second type is probabilistic and gives a probabilistic range of what could happen. Some scientists argue against the probabilistic way of presenting uncertainties because there are important limitations to our ability to project future climate conditions for adaptation decision-making (Hall, 2007). Uncertainties can only be quantified to a certain extent, depending on the time scale of interest. Epistemic uncertainty can generally be quantified within certain limits, e.g. 'unknown unknowns' cannot be quantified, stochastic uncertainty can only partly be quantified and human reflexive uncertainty is largely unquantifiable. Some authors argue that climate projections should not be the central tool to guide adaptation to climate change (Dessai, Hulme, Lempert, & Pielke Jr, 2009), whereas others state that it is essential that GCM projections are accompanied by quantitative estimates of the associated uncertainty (Giorgi, 2005; Murphy et al., 2004).

## 1.4 Communicating climate change uncertainty to decision makers

Projections of climate change are instruments used by decision makers for the development of climate change adaptations. The climate projections are used to assess the vulnerability of the natural and social system to future changes. To support decision making, these projections would ideally characterize clear future pathways with defined bounds of uncertainty. As described in paragraph 1.2, the projections of future climate change are limited by complex and large uncertainties, which cannot all be quantified. Although, it is not the primary role of the decision maker to understand the full complexity of climate change uncertainties, it is important that the decision maker understands the main uncertainties and how to use this knowledge for the development of robust adaptation measures. This proves to be a great communication challenge: climate scientists need to be transparent by delivering science that is perceived to be credible, salient and legitimate (Cash et al., 2003), whereas decision makers ask for understandable and usable science that can support decision making (Tang & Dessai, 2012; Tribbia & Moser, 2008).

To find ways to present uncertainties, it is important that scientists have a good overview of the demands of the decision makers. By the same token decision makers need to know what can be realistically expected of science. This match between science and policy is rather complex. Scientists expect that their knowledge can help inform decisions; however, many decisions continue to be made without scientific input (Sarewitz & Pielke, 2007). There are several reasons why scientific knowledge is not always used in decision making. On the one hand scientists frequently assume that their information and knowledge is reliable and useful without checking this assumption against reality (Jacobs, Garfin, & Morehouse, 2005; Morss, Wilhelmi, Downton, & Gruntfest, 2005; Moser & Luers, 2008; Sarewitz & Pielke, 2007). On the other hand the expectations of decision makers are not always realistic. Decision makers ask for certainty or a best estimate about the information that is given (Tang & Dessai, 2012; Tribbia & Moser, 2008). However, given the complexity of the climate system and the ecological and human systems with which it interacts, it is impossible to project future system states precisely (Lempert, 2002). Furthermore, it is not likely that the large uncertainties will be reduced in the near future (Dessai, et al., 2009; Maslin & Austin, 2012).

To make the scientific knowledge on climate change uncertainties more understandable and useful for decision making, there could be an important role for intermediaries, or boundary objects (Clark et al., 2011). The intermediaries create a space between science and policy to facilitate interaction, see Figure 1.2. The space created by the intermediary can be bridged and bring science and policy closer together, or it provides a neutral platform when science and policy are too closely linked, as some argue is the case for climate change (Weingart, et al., 2000). Intermediaries can exist in many different forms, well known examples are map tables and participatory scenarios (Ren, Ng, & Katzschner, 2011; Vervoort, Kok, van Lammeren, & Veldkamp, 2010).

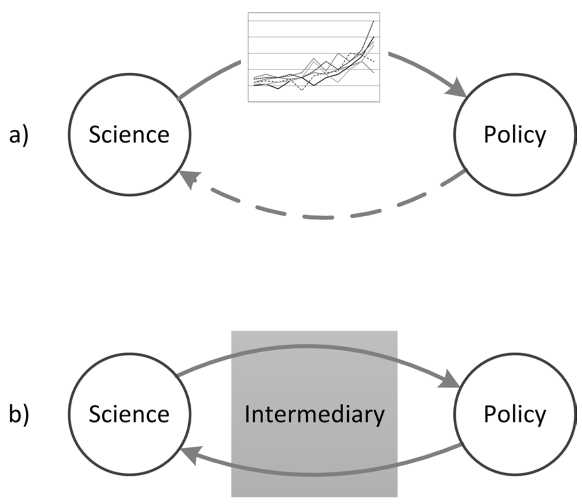


**Figure 1.2.** Different science and policy interaction modes. a) Science provides knowledge on uncertainties, which is inherently complex, and policy asks for understandable and usable knowledge. What science delivers in this mode does not connect to the demands of policy. b) Shows the role of an intermediary to improve the interaction between science and policy.

Model-based decision support tools are a specific type of intermediary that have become increasingly popular for linking environmental science to policy (White et al., 2010). Within the model-based decision support tools, simulation games have received increasing attention over the last four decades (Crookall, 2010). Simulation games represent dynamic models of real situations. Such simulation games can be used to transpose complex scientific information into understandable and tailored information that, through an interactive game, is tacitly connected to the target group (Haug, Huitema, & Wenzler, 2011). In simulation games, the scope of communication is broadened by linking them to technical and material processes that mirror natural and social systems (Kriz, 2003). Despite the increasing attention to simulation games, no studies have used simulation games in communicating about climate change uncertainties.

## 1.5 Research questions

Climate change concerns both natural and social science. Therefore, developing and implementing adaptation strategies to manage climate change risks requires collaboration between scientists and decision makers. Scientists provide projections of future climate change that are necessary for decision makers to make informed decisions about climate change adaptation. These projections of climate change are, however, characterized by large uncertainties. Part of this uncertainty is due to the embedding of human induced change in the natural climate variability. Communicating to decision makers about these complex uncertainties in an understandable way poses a great challenge. The principal aim of this thesis is to analyse the climate change uncertainties that are important to take into account for long term water management and to explore the communication of these uncertainties. Natural and social-scientific theories and methods will be used in the design of this study.

Based on the consideration above, three research questions have been formulated namely:

1. *Which type of uncertainty is dominant for explaining long term changes in average and extreme precipitation and discharge in the Rhine basin?*

The motivation for this research question is that for studying the role of climate change uncertainties it is first important to know more about the origin of these uncertainties. Knowledge about all the climate change uncertainties might byeinteresting from a scientific perspective, but is not very relevant for a decision maker. From this perspective it is meaningful to focus on the dominant uncertainties for flood risk management in the Rhine basin. In this study we focused on long term changes, which are defined as changes between the current and future climate at the end of the 21$^{st}$ century. We studied both changes in basin-average precipitation and discharge as well as extreme precipitation and discharge. Extreme precipitation and discharge are defined by the 90% quantile, the mean amount of precipitation above the 90% quantile ($E_{90}$) and by the values corresponding to high return periods up to 1,000 years.

2. *What is the impact of climate change uncertainties for the assessment of flood risk and the associated damage in the Rhine basin?*



Different methods exist to characterize uncertainties for the assessment of flood risk. In this thesis multi-model ensembles and different downscaling methods will be used to analyse the range of uncertainties for changes in flood risk. Changes in flood risk also have an impact on the expectations for the associated damage. Uncertainty analysis of flood damage will be done through a probabilistic framework for two case studies in the Rhine basin.

3. *What is the role of simulation games in the communication of climate change uncertainties between scientists and water managers?*

When the main climate change uncertainties for water management in the Rhine basin are analysed, the next step is to communicate this knowledge to water managers in a way that is understandable and facilitates the applicability of the information. The interaction between scientists and decision makers plays an important role in this communication. Simulations games can facilitate this interaction. The use of the game 'Sustainable Delta' for the communication about different types of uncertainty that are important for changes in flood risk will be assessed.

## 1.6 The Rhine basin

The Rhine basin is used as a case study area to examine methods to analyse and communicate climate change uncertainties. The river originates in the Swiss Alps, runs through Germany and flows into the North Sea at the Dutch coast. The Rhine basin is densely populated, with approximately 50 million inhabitants and includes highly industrialized areas. In the past 100 years there have been some major floods, with the most recent floods in 1993 and 1995 resulting in 1.4 and 2.7 billion euro damage (Engel, 1997; Te Linde, et al., 2011). In the flood prone areas, an estimated total of 1,500 billion euro of property is at risk. Continued implementation and improvement of flood and drought prevention measures, is even without climate change, a social and economic must.

In North-west Europe, were the Rhine basin is located, models and observations show a trend toward wetter winter conditions, both from mean precipitation as high rainfall events (Klein Tank et al., 2002; Klok & Klein Tank, 2009; Van den Besselaar, Klein Tank, & Buishand, 2012; Van der Linden & Mitchell, 2009). Especially, the increase in high rainfall events influences the probability of floods. An increase up to 30 % average discharge is projected for the Rhine river (Görgen et al., 2010; Hurkmans et al., 2010; Lenderink, van Ulden, van den Hurk, & Keller, 2007; Te Linde, et al., 2010). Also, Te Linde et al (2010, 2011) estimated an increase of the occurrence of an extreme 1250 year flood event in the Lower Rhine delta by a factor of three in 2050. As the economic and societal impact will increase in the future due to a growing number of people living in the flood prone areas, it is important to consider these changes for future flood management.

## 1.7 Thesis outline

The research questions are addressed in five (three published) scientific papers, which are presented in chapter two to six. The research framework of this PhD research is presented in Figure 1.3.

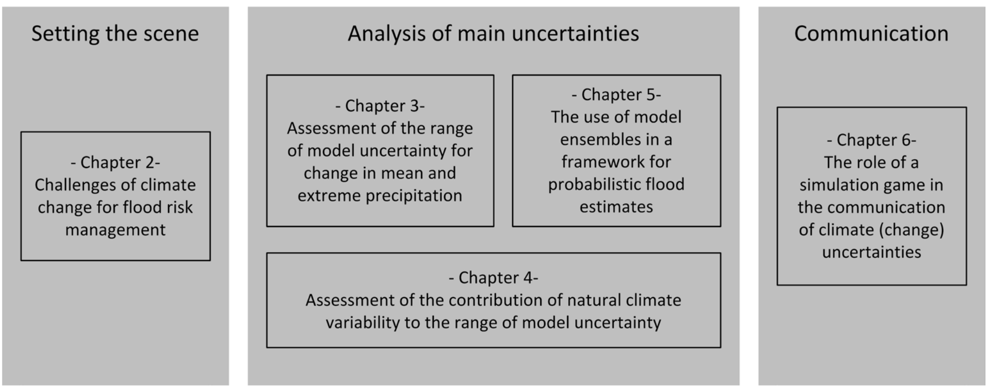


**Figure 1.3.** Research framework of this thesis.

Chapter 2 highlights the main challenges in the Rhine basin for flood risk management. The findings in this chapter were based on a literature review and expert interviews. In chapter 3, a variety of regional climate models was extended with several global climate models which allowed for a better assessment of the range of uncertainty. The advanced delta change approach, which allows for a quick processing of global climate model output, was developed further in chapter 3. In addition, the sensitivities of the advanced delta approach were explored. Chapter 4 elaborated upon the results of chapter 3 and compared the results of the ensemble of global climate models with the initial conditions ensemble of the ECHAM5 model (ESSENCE). The contribution of natural climate variability to the total model spread was assessed by means of analysis of variance (ANOVA). To derive results for long return periods, 3,000 year resampled time series were processed with the delta change approach. The resulting temperature and precipitation series were used as input for the HBV (Hydrologiska

Byråns Vattenbalansavdelning) model, which provided discharge time series. These series were analysed for long return periods. Chapter 5 was developed parallel to the study of chapter 3. The output of the climate models that were developed for chapter 3 were used as input for the study of chapter 5. A new methodology was presented in this chapter, in which a framework for probabilistic flood risk estimates was tested for two case study areas in the Rhine basin, thereby assessing the impacts of changes in flood risk. In chapter 6, the simulation game 'Sustainable Delta' was used as a boundary object in a series of workshops with water managers and students. The role of this simulation game for the communication of climate change uncertainties was assessed. Chapter 7 answers the research questions and reflects on the work of this thesis. Also recommendations for water management and a future outlook are presented here.

# Chapter 2

# Climate change risk management in transnational river basins: the Rhine basin

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# Abstract

Climate change is likely to have an impact on the discharge of the European river Rhine. To base adaptation strategies, to deal with these changing river discharges, on the best scientific and technical knowledge, it is important to understand potential climate impacts, as well as the capacity of social and natural systems to adapt. Both are characterized by large uncertainties, at different scales, that range from individual to local to regional to international. This review paper addresses three challenges. Dealing with climate change uncertainties for the development of adaptation strategies is the first challenge. We find that communication of uncertainties in support of river basin adaptation planning generally only covers a small part of the spectrum of prevailing uncertainties, e.g. by using only one model or scenario and one approach to deal with the uncertainties. The second challenge identified in this paper is to overcome the current mismatch of supply of scientific knowledge by scientists and the demand by policy makers. Early experiences with 'assess-risk-of-policy' approaches, starting from the resilience of development plans, suggests that this approach better responds to policy makers' needs. The third challenge is to adequately capture the transnational character of the Rhine river basin in research and policy. Development and implementation of adaptation options derived from integrated analysis at the full river basin level, rather than within the boundaries of the riparian countries, can offer new opportunities, but will also meet many practical challenges.

## 2.1 Introduction

### 2.1.1 The problem: too much water, or too little

Climate change is one of the major challenges society will face during this century. Temperatures are projected to increase up to 6.4 °C by 2100, which is expected to result in major changes in the atmosphere's energy balance and the hydrological cycle (Pachauri & Reisinger, 2008). Especially extreme events that result from these changes will impact human society, for example through heat waves, droughts and floods (Beniston et al., 2007). A recent example of the effect of climate extremes on water resources was in the summer of 2003, when a heat wave afflicted Europe. The result of this heat wave, with summer (June, July, August) temperatures exceeding the 1961–1990 mean by 3 °C (Schär et al., 2004), was not only a large number of casualties and other heat-related impacts, but also water resources were seriously affected. Large losses in crop yield and extremely low river discharges were reported in large parts of Europe. In Cologne, the river Rhine showed the lowest discharge since 1930 (Fink et al., 2004). The water level in the Rhine in the Netherlands and Germany reached critically low levels for power plants. A year earlier, in 2002, the opposite was happening when a large region, stretching from Germany and Austria to Romania and Russia, experienced severe floods. Although these events cannot directly or conclusively be attributed to climate change (Jacob & Van den Hurk, 2009), the IPCC's Fourth Assessment Report (Solomon et al., 2007) concluded that in the future anthropogenic climate change 'likely' to 'very likely' leads to increases in intensity and frequency of temperature and precipitation extremes. These phenomena are not constrained by watersheds or national boundaries, they can afflict large areas and many countries simultaneously and during these events conflicts between competing resource requirements, like drinking water, water for irrigation or cooling water for power plants, can be most intense. As a consequence, the urgency of a better understanding of risks of extreme hydrological events is increasing, both from a scientific and political perspective (Lehner, Döll, Alcamo, Henrichs, & Kaspar, 2006). In this review paper, we focus on three challenges of climate change adaptation for transnational river basin management using the Rhine river basin as a case study area: dealing with climate change uncertainties, addressing science-policy interaction problems, and capturing the transnational character of adaptation in transnational river basins.

### 2.1.2 Climate change adaptation in international river basins under uncertainty

The development of adaptation strategies has started just recently in river basins such as the Rhine, after the emergence of climate change and associated impacts as a reason for concern. This paper reviews the current situation and identifies key questions that should be addressed to facilitate the development of adaptation strategies. Formulating adaptation strategies poses a great challenge for both the scientific community and policymakers, particularly because of the incomplete understanding of natural and societal systems and the many associated uncertainties (Dessai & Van der Sluis, 2007;

Prudhomme & Davies, 2009). Dealing with uncertainties is not new to policy makers in the Rhine basin, because they have been dealing with water related uncertainties for decades. Floods and droughts are extreme events and it is hard to predict when they are going to happen and what the consequences will be. Policy makers and scientists have tried to estimate the probability of especially flooding on the basis of historical data and use these data to set the standards for safety levels. Adaptation strategies for river basins are necessarily not only based on historical data, as the magnitude and ubiquity of the projected hydroclimatic climate change requires going beyond stationarity as a central default assumption in water-resource risk management and planning (Milly et al., 2008). Adaptation strategies should therefore also be based on scenario analyses using climate impact models. These impact models, for example hydrological models, use temperature or precipitation simulations of global or regional climate models as input. In climate simulations used for the development of adaptation strategies, uncertainties at various levels of the assessment accumulate. The uncertainties are associated with future greenhouse emissions, the response of the climate system and with the spatial and temporal distributions of impacts (Dessai & Van der Sluis, 2007).

Policy makers and scientists need to deal with uncertainties in such a way that robust 'low-regret' or 'win-win' strategies can be formulated. When a strategy is robust, it performs relatively well, compared to alternatives, across a wide range of plausible futures (Lempert, et al., 2006). In addition, also criteria like e.g. flexibility, costs and social acceptance are relevant for the selection and design of adaptation actions (Aerts & Droogers, 2009; Lopez et al., 2009). Formulating robust strategies will only be possible if knowledge is effectively shared between the scientific climate community and policymakers at the many relevant governance levels, from local to international. Insufficient communication between scientists and policymakers and inadequate policy relevant information could lead to delay and inaction or to inefficient adaptation strategies (Alkhaled, Michalak, & Bulkley, 2007). Effective integration of science and decision making requires a tight coupling among research, communication and use of scientific output (Pielke Jr, Sarewitz, & Byerly Jr, 2000).

Risk management of climate change does not only pose a challenge for local policy makers, it is an issue relevant also at higher levels of governance: regional, national and in case of the Rhine basin also international. The Rhine flows through several countries and many governmental authorities with different territorial boundaries are involved. Climate adaptation strategies are therefore of international importance and one may expect that really effective risk management would benefit from cooperation between the riparian countries. Sadoff and Grey (2002) show in their paper also other benefits from cooperation between riparian countries, ranging from benefits to and from the river, like management of ecosystems and increased food production, to reduction of costs and eventually cooperation beyond river basin management issues alone. This paper will focus on the opportunities regarding climate risk management in the Rhine basin that could be provided by international cooperation, but it is important to be aware of other benefits.

### 2.1.3 Objectives of this review

In a transnational river basin, effective risk management requires a good match between information needs of policymakers and knowledge availability from the scientific community, robust management of uncertainties and transboundary cooperation. The objective of this paper is to take stock of current policy and science developments in the Rhine river basin and to address the following three questions:

- How are climate change uncertainties dealt with?
- How does a (mis) match between information needs and knowledge availability across different geographical and administrative scales stimulate or constrain effective adaptation policy development?
- What is the effect of (lack of) transboundary cooperation on climate change adaptation management?



Addressing these questions, priority research gaps to improve robust adaptation policy development in transnational river basins can be identified. This paper is based on a yet rather limited knowledge base. By structuring the problem of transnational climate change adaptation in a multilevel context we can give preliminary answers to these questions that may guide future research and policy development. We have based our findings on the review of available papers and documents and various informal contacts with particularly Dutch policy advisors and policy makers. The following sections will elaborate on the above questions, illustrated for the Rhine basin case study. Section 2.2 summarizes the framework and approach used for structuring this paper. Section 2.3 summarizes the scientific climate change knowledge base, focusing on spatial and temporal scales of climate models and introducing the uncertainties that are involved with climate change modelling. Section 2.4 addresses the (mis) match between information needs and knowledge availability. Section 2.5 examines the challenges that arise from transboundary cooperation in the Rhine basin. Section 2.6 discusses a Dutch case study and the final section presents preliminary responses to the above questions and identifies research gaps.

## 2.2 Approach

### 2.2.1 A framework for analysis

Figure 2.1 is used as an organizing structure for our paper. It shows interactions of the governance processes at different levels and the natural science processes at different spatial scales. The left hand side of Figure 2.1 represents the multi-level governance processes which, together with the scientific knowledge, result in the formation of adaptation strategies and measures. Multi-level governance in this context means that policy is determined by processes on several different territorial and administrative scales, varying from local, regional, national to European or even global (Marks &

Hooghe, 2004; Pierre, 2000). The focus of this paper is on the national and European level, but some of the conclusions can also be valid for the local and regional governance levels. The right hand side of Figure 2.1 represents natural science, where scientists simulate the impacts of climate change, usually with computer models. Socio-economic scenarios, such as those developed by the IPCC, are used to create emission scenarios, which serve as input for global climate models (GCMs). GCM outputs are downscaled, e.g. using regional climate models (RCMs) or statistical downscaling methods. In most cases, bias correction is required to improve the results. Impact models are then used to simulate the local impacts of climate change on social- and biophysical systems, for example hydrological models that simulate discharge for river basins.

Adaptation strategies are partly based on the results of these models. When, for example, the result of the modelling on the right hand side of Figure 2.1 indicates that it is likely that river discharges will increase, water managers can increase the height of dikes, which is in this case an adaptation strategy. Another example is if water levels are projected to decrease, and measures are required to adapt inland shipping practices. However, adaptation choices will not only depend on the modelling result, but also on other factors, like costs, impacts on environment, public response and acceptance, technical feasibility and demographic and water use changes (Lopez, et al., 2009). These factors will be part of the negotiations in the governance process. Water managers need information about the duration, magnitude, frequency and timing of future drought and flood relative to past and recent events, but also about how adaptable the natural and human systems are to these changes (Lopez, et al., 2009; Palmer et al., 2009). The development of adaptation strategies in the Rhine basin that are robust across a range of possible future changes can be achieved by a good match between the supply and demand of scientific knowledge.

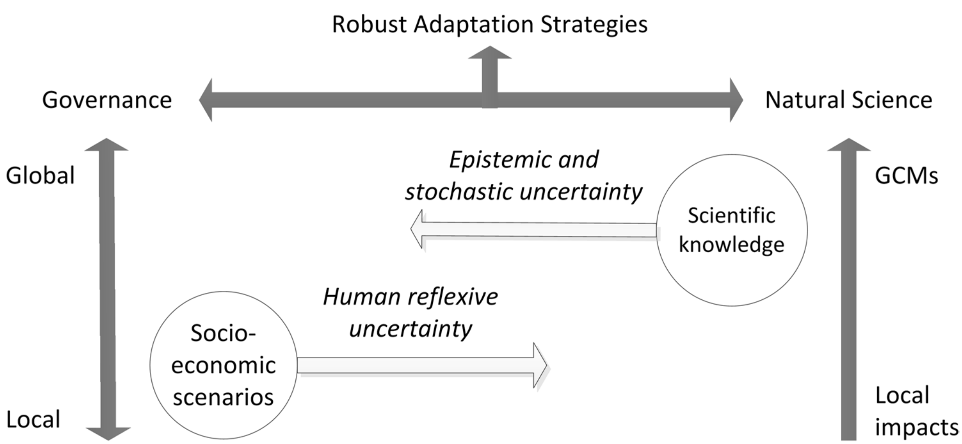


**Figure 2.1.** Interactions of science and governance at different scales fo knowledge of robust adaptation strategies

This process is displayed in the centre of Figure 2.1. Supply and demand for information emerge from complex networks of individuals and institutions with diverse incentives, capabilities, roles and culture. In this paper we conceptualize science, in this case results of climate and impact models, as 'supplier' of knowledge and information. The policymakers who seek to apply knowledge and information to achieve specific goals, have a 'demand'. For this paper, we focus on the development of climate adaptation strategies as a policy goal.

### 2.2.2 Types of uncertainties



Three types of uncertainties can be distinguished that determine the uncertainty range of future climate and impact projections: (a) incomplete knowledge (epistemic uncertainty), (b) unknowable factors (stochastic uncertainty, e.g. intrinsic variability in the climate system) and (c) human reflexivity (Dessai & Hulme, 2004). Epistemic and stochastic uncertainty are part of the scientific climate model output. The third type of uncertainty, human reflexivity, is introduced by the social system. Humans can reflect critically on information and change their behaviour. Society is likely to act upon scientists' projections that climate will change (Dessai & Hulme, 2004). The behaviour of society influences the climate and impact projections because the social-economic and associated emission scenarios change as a function of the policy responses: when scientists project that the climate will change due to anthropogenic greenhouse gas emissions it is likely that mitigation measures will be taken. These measures influence the climate scenarios that have been developed and in that sense influence the range of climate change impacts that are projected. Policy makers at different levels are confronted with the scientific output of climate models. At higher administrative levels this knowledge is mostly used to support the formulation of rather broad adaptation strategies, like the Dutch and German National Adaptation Strategies, while at local levels it provides input into the design of more concrete adaptation measures. Concrete adaptation measures can be, for example, building houses that are resistant to flooding or increasing the height of dikes, or changing rules for spatial planning in flood-prone areas. This process requires adequate 'vertical interaction' between different administrative levels in the governance system and 'horizontal interaction' with the scientific community at each level.

Whilst Dessai and Hulme's uncertainty types are formulated from a scientist's perspective, for a policy maker, who has to use information about climate change in order to formulate adaptation measures, climate change can be associated with conditions of deep uncertainty. By deep uncertainty we mean both scientific and social factors that are difficult to accurately define and quantify (Kandlikar, Risbey, & Dessai, 2005). Deep uncertainty is present at all levels of the uncertainty typology of Dessai and Hulme as in every level uncertainties exist that cannot be quantified or accurately defined. The most deep uncertainty exists in the human reflexive uncertainty, as this is not quantifiable other than in a hypothetical scenario context. Lempert et al. (2004) uses deep uncertainty to refer to conditions that policymakers do not know, or do not agree on regarding (1) the appropriate model to describe interactions among a system's variable, (2) the probability distributions to represent uncertainty about key parameters in the models, or (3) how to value the desirability of alternative outcomes. When uncertainty is such an important variable, it makes sense for policymakers and scientists to identify strategies that are robust, i.e. perform well over a wide range of different futures. Ideally these strategies would also be 'win-win' or no-regret, but in practice, for strategies that mainly address climate change impacts there can be opportunity costs, trade-offs, or externalities associated with adaptation actions so it is better to refer to such interventions as 'low regret' (Wilby & Dessai, 2010). In many cases however, climate change is just one of many other factors that determine strategies or investment decisions, and in those cases win-win or no regret options may be identified. In our review we first focus on the right hand side of Figure 2.1, then the left hand side. The danger of examining both sides separately is that interactions within the whole system are missed and the complete picture is lost. For the sake of simplicity of this review paper we decided to deal with the two sides subsequently and in the final section to focus on the whole integrated system.

### 2.2.3 Dealing with uncertainties: 'predict-then-act' approach versus 'assess-risk-of-policy' approach

As climate change is a very complex problem, policy makers turn to scientists for specific advice. Because of the large uncertainty of climate change projections, there is an increasing consensus that it is important to communicate and deal with this uncertainty. There is less consensus, however, on the best practices for doing this (Patt, 2009). Different academic disciplines offer diverging advice on this subject. For this review, we distinguish between two fundamentally different approaches (Dessai & Hulme, 2004).

The first approach is the 'predict-then-act' approach sometimes also referred to as the top-down approach, which is shown in the left hand side of Figure 2.2. It focuses on downscaled global climate change scenarios and it is strong in dealing with statistical uncertainty (Dessai & Van der Sluis, 2007). For this approach one or more climate scenarios are used as starting point for an impact assessment. The goal is then to derive an optimum adaptation strategy, based on the results of the impact assessment, seeking to find a solution that performs best contingent to a particular view (Lempert & Collins, 2007). In Figure 2.2 the 'predict-then-act' approach has a focus on climate change scenarios and climate model outcomes from the right hand side. Future developments are projected as accurately as possible and research supporting this approach aims at decreasing uncertainties. The approach is widely used and accepted. The IPCC and most national and region adaptation assessments in Europe, for example, take this approach, starting with impact assessments on the basis of downscaled climate modelling results (Wilby et al., 2009). The second approach called the 'assess-risk-of-policy' approach or sometimes the bottom-up approach, is shown in the right hand side of Figure 2.2. It does not take climate projections as the starting point, but the vulnerability of the system itself, its development ambitions and its resilience. Resilience can be defined as the ability of the system to absorb disturbances (Aerts & Droogers, 2009). This approach takes into account a broader set of issues from the start, and is stronger in coping with ignorance and surprises. It seeks adaptation strategies that can make the system less vulnerable to uncertain climate change impacts and unpredictable variations in the climate system (Dessai & Van der Sluis, 2007). In Figure 2.2 this approach starts at the top by assessing the vulnerability of the system and the available adaptation strategies that increase the resilience of the system. The 'assess-risk-of-policy' approach allows best for the evaluation of the robustness of possible strategies. An adaptation strategy is robust when it works good across a wide range of future scenarios (Lempert & Collins, 2007). This paper reviews the use of both approaches in the Netherlands in Section 2.6.



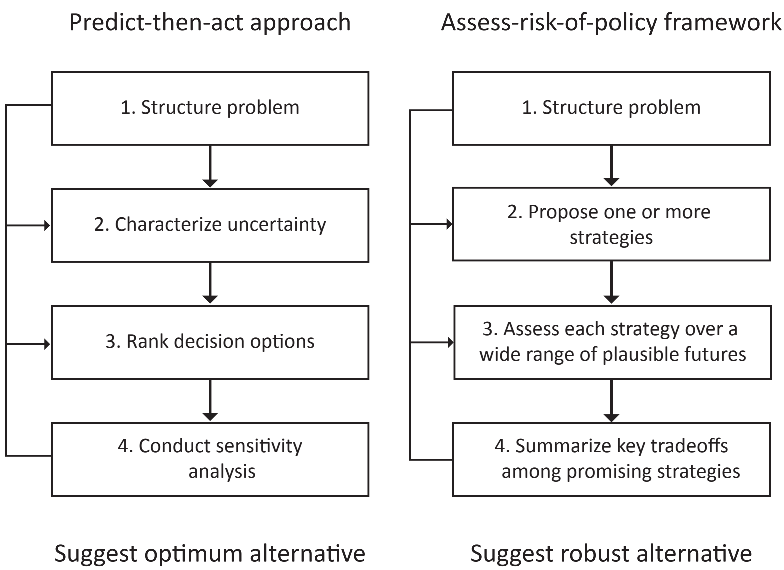


**Figure 2.2.** Two approaches for dealing with uncertainty adopted from Dessai et al. (2009)

## 2.3 Knowledge availability and uncertainties in the Rhine basin

### 2.3.1 Case study area: Rhine river basin

The river Rhine (Figure 2.3) originates in the Swiss Alps as a mountain river, fed by glacier water, snowmelt and rainfall. From Switzerland it flows through Germany, France and the Netherlands into the North Sea. Currently, the total catchment area of about 185,000 km$^2$ and the length of 1238.8 km, makes the Rhine the longest river in Western Europe. In the course of time, along the Upper Rhine the discharge section has been reduced from a width of about 12 km to some 200–250 m. The course of the Rhine have been shortened by 82 km, the construction of 8 dams for hydropower and two storage dams has reduced the surface of the flood plains of the Upper Rhine area by 130 km², which was 60% of the total retention area between Basel and Iffezheim. Today the Rhine disposes of less than 15% of the original flood plain (ICPR, 2009b). The Rhine basin includes densely populated and highly industrialized areas with approximately 50 million inhabitants.


**Figure 2.3.** Rhine basin (Ecology and Society, 2011)

The river is of great economic and environmental importance for the riparian countries. Its water is used for many sectors, such as hydropower generation, agriculture and industry and domestic water use. About 20 million people depend on Rhine water as a source of drinking water (Aerts & Droogers, 2004) and it is the busiest waterway for inland navigation in Europe (Middelkoop, et al., 2001). In the flood prone areas, an estimated total of about 1,500 billion Euro of property is at risk (Klein, Douben, Van Deursen, & De Ruyter Van Steveninck, 2004). Continued implementation and improvement of flood and drought prevention measures is an economic and social must.

### 2.3.2 Temperature and precipitation projections for the Rhine basin

The changes in the weather system above Europe, which serve as input for hydrological models, have been analysed in different studies. An overview by Beniston et al. (2007) presented changes in extreme events that are most likely to affect Europe in the coming decades. The results showed that the intensity of extreme temperatures increases more rapidly than the intensity of more moderate temperatures due to increases in temperature variability. The simulations showed that heavy winter precipitation is projected to increase in central and northern Europe and decrease in the south. In a high resolution simulation (10 km) over the Rhine basin, the regional pattern of temperature change displays a stronger warming in the south and south-east of the domain covering Germany, the Alps and Switzerland for the time period 2071–2100 compared to 1961–1990. This is associated with a decrease in precipitation in summer. An increase in winter precipitation in south and south-west regions was simulated. Less precipitation will fall in the occurrence of snow (Jacob & Van den Hurk, 2009). The 2006 scenarios of the Royal Netherlands Meteorological Institute (KNMI) (Van den Hurk et al., 2006) project a summer decrease of the wet day frequency of up to 10–20% and an increase of wet day precipitation in the winter of 4–9% for the Netherlands. These regional changes were obtained by scaling three GCM projections with ten RCM outputs. The results above have been confirmed by a recent study of the International Commission for Protection of the Rhine (ICPR) which assessed the state of knowledge on climate change. Because of the high uncertainty in projected precipitation, the uncertainty in the impact indicators that are linked to precipitation and water supply is high (Jol, Raes, & Menne, 2009).

### 2.3.3 Runoff projections for the Rhine basin

The potential impact of climate change on the hydrological regimes of the river Rhine has been assessed quantitatively in several studies. To estimate the impact of climate change on river discharge, different scenarios of future meteorological conditions are used as input of a hydrological model. As a scale mismatch exists between the coarse resolution of a GCM and the regional catchment scale, the GCM results have to be downscaled. This is usually done with statistical or dynamical downscaling techniques (Lenderink, Buishand, & Van Deursen, 2007). Both methods can generate different results adding uncertainty (Jacob & Van den Hurk, 2009; Lenderink, van Ulden, et al., 2007), For the Rhine basin different IPCC emission scenarios (Nakicenovic et al., 2000), driving GCMs and hydrological models are used. The hydrological model used most is RhineFlow (Van Deursen & Kwadijk, 1993). Table 2.1 shows that studies published on this subject show different results ranging from an average increase in discharge of 13% or even up to 30% at the end of this century. Drought projections show similar variation ranging from an average decrease in discharge of 5% to 40% in

2100. The simulated results in these publications do have a large uncertainty range and for each study only a limited number of driving models has been used, but the results appear to agree at least in sign and order of magnitude. A detailed and meaningful comparison between the outcomes of the studies is not possible, because not only the underlying assumptions and input data are different, but also the reported output differs in terms of the choice and definition of indicators and time scales.

The overview above and Table 2.1 show that studies, simulating discharge for the river Rhine mostly use one or two IPCC scenarios, initially mainly the older IS92a, later the IPCC SRES A2 or A1B scenario. The IS92a and A1B scenario can be regarded as 'middle' scenarios, while A2 represents one of the highest emission scenarios (Nakicenovic, et al., 2000), suggesting an intentional move from 'best guess' to 'worst case' scenario selection, around 2005. Because the approach of these studies is different their results cannot meaningfully be compared, which makes it difficult to appreciate their relevance for policy purposes. This suggests that harmonization of definitions, methods and reported results would be highly desirable from both a scientific and policy perspective.

**Table 2.1.** List of published research on hydrological simulation of the influence of climate change on discharge of the river Rhine. Caution is warranted in comparing the projected change in discharge because of the differences in the choice of specific variables, time scales and model assumptions. In addition, only the main findings are summarized here (for more detailed information or specifics about the simulations, the authors refer to the papers).

| Study | Year | GCM | IPCC Scenario | Hydrol Model | Spatial resolution RCM | Temporal resolution | Projected change in Rhine discharge |
|---|---|---|---|---|---|---|---|
| (Kwadijk & Rotmans) | 1995 | CLIMAPS | BaU & AP | RhineFlow | 0.5° x 1.0° | 2100 | Up to 20% increase in average winter discharge and up to 15% decrease in summer discharge, BaU scenario at Lobtih |
| (Middelkoop, et al.) | 2001 | UKHI/ XCCC | IS92a | RhineFlow | 0.5° x 0.5° | 2050 | Annual peak flows increase 20 % in winter and decrease 5% in summer in the Lower Rhine |
| (Shabalova, Van Deursen, & Buishand) | 2003 | HadRM2 | IS92a | RhineFlow | 50 km | 2080-2099 | Increase of 30 % average winter discharge and a decrease of 30% or even up to 50% in summer at Lobith |
| (Jasper, Calanca, Gyalistras, & Fuhrer) | 2004 | HadCM3 | A2-B2 | Wasim | - | 2081-2100 | Average increase of 14% to 31 % in two Alpine Rhine basins in winter and 16-33% decrease in summer |
| (Klein, et al.) | 2004 | HadCM3 | A2-B2 | RhineFlow | - | 2070-2099<br>2010-2039 | Increased winter discharge and decreased summer discharge, no percentages or numbers given |

2

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (Menzel, Thieken, Schwandt, & Bürger) | 2006 | HadCM3 | IS92a | HBV-D | - | 2061-2095 | Increased winter discharge, no percentages or numbers given |
| (Lenderink, Buishand, et al.) | 2007a | HadRM3H | A2 | RhineFlow | 50 km | 2070-2099 | Increase of about 30% in average winter discharge and a decrease of 40 % in average summer discharge at Lobith |
| (L.P. Graham, Hagemann, Jaun, & Beniston) | 2007 | HadAM3H | A2 | HD/Wasim | 50 km | 2071-2100 | Mean decrease in summer discharge up to 40%, increased winter discharge at Cologne |
| (Hurkmans, et al.) | 2010 | ECHAM-5 | A2-A1B and B1 | VIC | 10 km | 2052-2100 | Increase of 30% in average winter discharge and decrease of 30% in summer discharge at Lobith |
| (Te Linde, et al.) | 2010 | ECHAM-5 | A1B | HBV | 25 km | 2050 | Average discharge increase of 13% in winter, decrease of 17.4% in summer months at Lobith |
| (Görgen, et al.) | 2010 | Mostly ECHAM-5 | Mostly A1B | HBV | 25km | 2050-2100 | Average winter discharge increase up to 25% and summer decrease up to 30% for different Rhine gauging stations |

### 2.3.4 Uncertainties related to climate modelling and simulated impacts

The uncertainties that are part of the discharge simulations for the river Rhine, result from a cascade of individual uncertainties (Giorgi, 2005). The first part of this cascade consists of selecting an emission scenario, like the SRES A1B or A2 scenarios. The second part relates to the applied GCM. The choice of the driving GCM generally provides the largest source of uncertainty in downscaled scenarios (Dessai, 2005; Fowler, et al., 2007; Leander, Buishand, Van den Hurk, & De Wit, 2008; Menzel, et al., 2006; Prudhomme & Davies, 2009). This means that the uncertainty range of, for example, one GCM forced by different emission scenarios is lower than that of one emission scenario forcing different GCMs. Often only 50% of the changes predicted by GCMs can be significantly attributed to the signal of the GCM projections (Prudhomme & Davies, 2009), the other changes can be, for example, attributed to natural variability. However, most studies on the impacts of climate change on the river Rhine to date only make use of one driving GCM. This indicates that a lot of uncertainty is unknown, as using multiple driving GCMs could result in significantly different outcomes (Knutti, Furrer, Tebaldi, Cermak, & Meehl, 2010). The third source of uncertainty comes from the choice of downscaling technique, which could be statistical, or dynamical using RCMs. On time scales of decades, which are interesting from an adaptation point of view, uncertainties from the choice of downscaling techniques and of emission scenarios are generally smaller than uncertainty related to the choice of GCM. Sensitivity analysis using alternative climate models or scenarios are usually not reported. The reasons for this may be that hydrological modellers have resource or time constraints, or arguments which would justify the selection of a particular representative or worst case scenario, but this is not discussed in the papers that we have examined. Outputs from RCMs cannot be used in impact studies without first applying a bias correction (Fowler, et al., 2007). The use of bias correction can add another level of uncertainty to the downscaling part as the used method influences the resulting discharge (Van Pelt, Kabat, Ter Maat, Van den Hurk, & Weerts, 2009). The fourth source of uncertainty arises from the use of hydrological models. This part can be divided in three sources of uncertainty: random or systematic errors in the output data, uncertainty due to sub-optimal parameter values and errors due to incomplete or biased model structure (Butts, Payne, Kristensen, & Madsen, 2004). The final and fifth source of uncertainty is related to the observational data, that is used for bias correction, but also for validation and calibration of the hydrological model. Often observations contain measurements errors or the number of observations is too little to, for example, properly validate the model, which adds more uncertainty. These uncertainties are all examples of epistemic and stochastic uncertainty.

### 2.3.5 Uncertainties related to time scale

Uncertainties in climate projections vary with the averaging period over which the climate is defined and with the lead time of the projection. On the time scale of a few years to a few decades ahead, regional and seasonal variation of mean temperature in the climate will be strongly influenced by natural and internal variability. This means there is less certainty about the cause of change. The human climate signal will be even harder to discern at river basin scale (Wilby, et al., 2009). It is important to know the extent to which the climate events, like precipitation which influences river discharge, are the product of natural variability, or are the result of potentially irreversible, forced anthropogenic climate change (Hurrell et al., 2009). The changes in river discharge can also be related to non-climate factors, such as land-use changes or river basin management practices. To date, there is little knowledge about how to separate the natural and anthropogenic climate change signals for short-term forecasting. On this short time scale, uncertainties in initial conditions dominate the overall uncertainty of the projection. On longer time scales, anthropogenic emissions of greenhouse gases and aerosols, relating to scenario uncertainty, are a larger source of uncertainty than the initial conditions. A third type of uncertainty is the process and parameter uncertainty, this type increases in the first decade, but then stays relatively stable. The net effect of all these uncertainties is that the fractional uncertainty, defined as the prediction error divided by its central estimate, is smallest on the 30 to 50 year time scale (Cox & Stephenson, 2007).

## 2.4 The (mis) match between information needs and knowledge availability

Political systems are caught in four to five year democratic cycles, while future climatic impacts are calculated for time scales that are much longer. In Table 2.1 it is shown that most studies focus on at least the year 2050. Policymakers are more interested in changes for the next couple of years, or what these changes mean for decisions they have to make on a short timescale. This is not true for all policymakers, as there are policymakers who are not chosen every four or five years and law and legislation are designed for longer term. Despite this, earlier studies showed that climate change is generally not seen as most important in the short term (Arnell & Delaney, 2006; Ivey, Smithers, De Loë, & Kreutzwiser, 2004). Other political priorities dominate and it is easier to make decisions on issues that have a short time span. Furthermore, the short term socio-economic factors determining adaptive capacity are at least as important for vulnerability as climatic changes. Temporal mismatches occur when the short term temporal scale of policy makers and the long term temporal scale of the climate processes do not align (Cumming, Cumming, & Redman, 2006). Furthermore, Table 2.1 shows that the spatial resolution of RCMs of the studies has a maximum of 50 km. The spatial uncertainty of grid cells can be decisive for hydrological analysis of the river basin, making it difficult to make judgments on regional levels (ICPR, 2009a). This also indicates that this low resolution does not always match the territorial boundaries of policymakers. The output of the hydrological model is usually a projected discharge for a specific location, like, for example, Lobith, the place where the Rhine enters the Netherlands. Local policymakers may need much more specific information. Temporal and spatial scaling complicate effective knowledge sharing between climate science and policy. This is further complicated by the fact that adding more spatial and temporal detail, often also adds more uncertainty (Alkhaled, et al., 2007). Therefore, the choice of level and type of detail included in risk assessments should be driven by both scientific experts and policy makers, but this is often not the case.

Next to scaling and temporal issues, the representation of uncertainty for guiding decision-making faces a number of challenges. First, most studies quantify only a limited number of the types of uncertainties that have been mentioned in the previous section, often the total uncertainty is not clearly represented. Lack of transparency regarding the assumptions and uncertainties can lead to misunderstandings in the science-policy interface on the nature of the knowledge (Van der Sluijs, 2005). Second, the communication and representation of uncertainties is under a lot of debate. For example, the UK is the first country to present climate change projections for policy applications in a probabilistic framework (Jenkins et al., 2009). Some scientists are against this way of presenting uncertainties, as there are important limitations to our ability to project future climate conditions for adaptation decision-making (Hall, 2007): uncertainties can only be quantified to a certain extent. Others find it is essential that GCM projections are accompanied by quantitative estimates of the associated probability (Giorgi, 2005; Murphy, et al., 2004; Wigley et al., 2003). Adding to this debate, Gawith et al. (2009) explain that the experience with UKCP09 has taught that the provision of probabilistic climate scenarios must be accompanied by on-going guidance and support. Another lesson from UKCP was that on-going dialogue between those providing the scenarios and the communities using them is essential. Both lessons were motivated by the experiences from the UKCP02 program, which showed that users frequently chose the Medium-High climate change scenario, because it had the most detailed information and it was seen by some as presenting a 'middle road' or a 'safe' choice. It was also less resource intensive than having to apply four scenarios (Gawith, et al., 2009). This experience and debate demonstrates that there is still much to be researched in communicating climate uncertainties and that interaction between scientists and policymakers is fundamental to constructively meet the challenges associated with climate change projections. Standard methodologies to include uncertainties in potential changes and assess their impact on projected estimates have yet to be developed (Prudhomme & Davies, 2009). There remains a question as to whether it is possible to develop such a generic method that will fit all situations. Until then, the debate about how to present and how to manage uncertainties can be confusing and may make it more difficult for policymakers to formulate adaptation strategies on the basis of available scientific knowledge.

## 2.5 Transboundary cooperation on adaptation management in the Rhine basin

### 2.5.1 The European level: European Union policies

As to the management of water in the Rhine basin, policies at all levels are relevant: EU, transnational, national and local. Up to recently, climate change impacts have not been a major concern in EU water policy (Leipprand et al., 2007). At the European level, legislation that is relevant for climate adaptation regarding the water sector are the Water Framework Directive (WFD) and the Flood Directive. The WFD requires a river basin management plan to be established for each river basin district. Although originally not explicitly included in the legislation, this management framework allows for the inclusion of climate change adaptation issues and must be updated every six years. In 2009, the Commission issued a Guidance document on how to integrate climate change into river basin management plans (EU, 2009a). In 2015 the first management cycle of the WFD and the river basin management plans ends. At that time the programmes can be updated and the latest insights as to climate change impacts taken into account. The Flood Directive requires Member States to coordinate their flood risk management practices in shared river basins and to avoid taking measures that would increase the flood risk in neighbouring countries. The Directive has been published in 2007 and it requires Member States to carry out a first assessment by 2011 to identify those river basins and associated coastal areas that are at risk of flooding. The flood risk management plans should be finished by 2015. As they only contain a limited number of explicit references to climate change impacts, these existing policy instruments can be used as a starting point but have to be developed further. While to date little has been done to mainstream adaptation into the relevant EU policies (Leipprand, et al., 2007), recently the European Commission released a White Paper in which a framework is set out to reduce the EU's vulnerability to the impact of climate change in general (EU, 2009b). It provides suggestions for a stepwise development of European adaptation policy, including the mainstreaming of adaptation into sector policies such as those related to water management. The intention is that phase 1 (2009–2012) will lay the ground work for preparing a comprehensive EU adaptation strategy to be implemented during phase 2, commencing in 2013.

### 2.5.2 The river basin level: International Commission for Protection of the Rhine

In the case of the Rhine, a river-basin-wide institution has been established, notably the International Commission for Protection of the Rhine (ICPR), a platform for the riparian countries to discuss the sustainable development of the Rhine. The ICPR was initiated in the 1950s following concerns about pollution of the river and the implications for drinking water supply. The IPCR has no formal authority to carry out measures, the decisions taken are not legally binding and implementation is the responsibility of member states (ICPR, 2009b; Van Ast, 2000). The Flood Action Plan, which has been established as part of the Rhine 2020 programme on sustainable development of the Rhine by the ICPR in 1998, aims to reduce risks of flooding by, for example, creating retention areas. Such measures would reduce vulnerability to climate change as well, although in 1998 there was no explicit mentioning of climate change adaptation yet. On October 18th 2007 the Conference of Rhine Ministers decided to jointly develop adaptation strategies for water management in the Rhine watershed, in order to cope with the challenges of climate change. An international expert group (KLIMA) has worked on an analysis of the state of knowledge on climate changes so far and on the impact of climate change on the water regime in the Rhine watershed (ICPR, 2009a), but no concrete adaptation plans have been developed yet.



### 2.5.3 The national level: German and Dutch adaptation plans

Adaptation strategies at the national level in Germany are mainly related to strategic action. The implementation of federal laws is usually delegated to the federal states (Länder) which have the primary right to develop and implement legislation in the field of water protection (Kastens & Newig, 2008). The German National Adaptation Strategy (NAS) has been adopted by the Cabinet in 2008. The NAS aspires to integrate the work that is already in progress in various ministries (Swart et al., 2009). It creates a framework for adaptation to climate change, but it will require further specification. The Federal Government is therefore aiming to present an Adaptation Action Plan drawn up jointly with the Federal States by the end of March 2011. The NAS confirms the responsibility of the Länder for water safety, with the federal government playing a role in providing knowledge and tools. Regarding international cooperation the German NAS only states that the Federal Government will coordinate the German position. In the Netherlands the government has formulated a National Adaptation Strategy in 2007 called 'Make Space for Climate'. The government is currently working on a National Adaptation Agenda. The strategy documents are starting points for formulating more substantive climate adaptation policy. The document relates primarily to spatial measures, although raising awareness and identifying gaps in knowledge are also part of the strategy (Swart, et al., 2009; VROM, 2007). Attention for international cooperation is limited to a few sentences that indicate the importance of cooperation with other countries. How this should be managed is not elaborated. The Netherlands forms a delta where major European rivers flow into the North Sea, which makes the country vulnerable to flood risk. Therefore, complementary to the NAS, the Dutch government requested an independent Committee of State (the Delta Committee) to advice on flood protection and flood risk management in the Netherlands for the next century. The Delta Committee formulated twelve recommendations to secure the country against flooding on the short and medium term. The recommendations focus on this century, but the Committee's report also includes a long-term vision to 2200 (DeltaCommittee, 2008; Kabat et al., 2009). An important recommendation of this Committee is the advice to increase safety levels by a factor 10. Although in the EU White Paper transboundary or international cooperation is an important topic, in the national adaptation strategies of both the Netherlands and Germany, this seems to have little priority as yet. Contacts between scientists and policy makers in the two countries on climate change and the Rhine appear to remain limited to a few research projects of limited length, such as Rheinblick2050, some working groups of ICPR and ad-hoc meetings. At the regional level there is some cooperation between the Dutch province Gelderland and the German Land Nordrhein Westfalen. This could be an inspiration for other provinces and Länder to start cooperating more.

### 2.5.4 Institutional and cultural challenges

Adaptation actions take place within hierarchical structures; administrations at different levels interact with each other. Actions are therefore determined (facilitated or constrained) by institutional processes such as regulatory structures, property rights and social norms associated with rules in use (Adger, Arnell, & Tompkins, 2005). Transboundary cooperation is restrained by several differences between the Netherlands and Germany.

In Table 2.2 the differences between Germany and the Netherlands regarding water policy and risk perception are shown. The table is divided in three different factor categories as adopted from Dieperink (1997) and Becker et al. (2007). Safety levels, meaning the recurrence level of a design discharge in years, in the Netherlands are much higher than in Germany, see also Table 2.3. Both countries take a different approach in dealing with uncertainties in flood risk management. The Dutch strategy follows a more protective approach, whereas Germany puts emphasis on precaution and damage reduction (Becker, et al., 2007). In the Netherlands floods are calamities with large financial and social consequences, in Germany people are more used to floods and in most areas the consequences are less severe (Steenhuisen, Dicke, & Tijink, 2006). The diverse perceptions on flood risk and the corresponding safety levels can be explained by differences in potential flood impacts. In the Netherlands more than 8.5 million people live in flood risk areas, that is more than 50% of the total population. In Germany, over 2 million people live in flood risk areas, which is less than 2.5% of the total population. The financial damage in case of a flood is estimated at 130 billion euro for the Netherlands, compared to 34 billion in Germany (ICPR, 2001). This estimate is based on all the properties that are located in flood risk areas. Dutch inhabitants expect higher authorities to take action regarding flood safety, in Germany floods are perceived as regional or local events against which measures have to be taken by officials as well as individuals (Becker, et al., 2007).

The Dutch government has adopted legal obligations concerning flood prevention and damage Compensation that are stricter than in Germany. In Germany this legislation differs between Länder (Raadgever, 2005). The competence for water management in the Netherlands is primarily allocated to the national level, while in Germany the competence is allocated to the sixteen Länder, making the Länder of central importance for transboundary issues. Although the Länder coordinate policy and legislation concerning water management in the Länder Water Working Group (LAWA), the fact that Germany is divided in sixteen authorities makes harmonization of water management in the whole Rhine basin more difficult (Steenhuisen, et al., 2006). The Rhine basin does have a history of successful international cooperation, due to the pollution of the Rhine. The quality of the water in the river has been under debate since the late 19th century and since 1950 there have been formal and informal consultations between the riparian countries. In 1960 and 1970 the pollution was so heavy that the river Rhine was called the 'sewer of Europe'. Since then, different Treaties have been established and the quality of the Rhine improved significantly. Crucial for the development of this Rhine regime has been a strong involvement of downstream parties, in combination with willing upstream parties (Dieperink, 2000). International formal interactions can be a competence struggle, but due to long lasting cooperation, trust between the riparian countries has developed (Raadgever, 2005). Although collaboration and information exchange on climate change has been rather ad hoc until now, experiences in the past suggest that also in the area of climate change adaptation opportunities for more structural cross-boundary collaboration in policy and science exist and can be enhanced.



**Table 2.2**. Differences regarding water policy and risk perception

| Category | Germany | Netherlands |
|---|---|---|
| Cognitive | Lower safety levels<br>Damage reduction<br>More used to floods, less financial and social consequence<br>Regional and individual responsibility | Higher safety levels<br>Protective approach<br>Large financial and social consequence<br>National responsibility |
| Institutional | Less strict legislation<br>Competence located at Länder | Stricter Legislation<br>Competence located at national level |
| Riparian position | Upstream | Downstream |

## 2.6 Dutch Case: evolution of design discharge

Important policy variables in river basin management are politically agreed safety levels and design discharges derived from scientific analyses. Safety levels refer to the frequency of flood events that is considered to be acceptable. The amount of water per second that can be associated with these safety levels and which statistically has a certain probability to occur ('design discharge') is used to design adaptation or flood protection measures, e.g. to determine the necessary height of a river dike. Both safety level and design discharge differ between countries and vary over time as scientific insights and political priorities evolve.

**Table 2.3.** Current safety levels and design discharge for German and Dutch part of the Rhine basin

| Part of river basin | Safety level (recurrence interval in years) | Design discharge ($m^3s^{-1}$) |
|---|---|---|
| Oberrhein (Germany) | 110-1,000 | 5,500-7,300 |
| Niederrhein (Germany) | 200-500 | 12,900-14,800 |
| Rhinedelta (Netherlands) | 1,250 -10,000 | 16,000 |

Table 2.3 shows different safety levels and corresponding design discharges for Germany and the Netherlands. The safety levels in the Netherlands are up to tenfold higher than in Germany. The Dutch norms are legally binding at the national level, while the German norm can differ between Länder, depending on historic water levels and local initiatives (Steenhuisen, et al., 2006).

The estimation of the probability of an extreme event, that corresponds to a high safety level is far from trivial (Te Linde, et al., 2010). Safety levels for the Rhine are relatively high and with only 110 years of observed discharge data available, statistical extrapolation leads to very high uncertainties (Klemeš, 2000a). For recent applications, more sophisticated approaches have been developed that combine weather generators with hydrological models (Buishand & Brandsma, 2001), to create such long discharge series that extrapolation is redundant. However, this approach is also under debate, as it requires hydrological modelling of extreme events, far beyond available time series of historic events (Te Linde, et al., 2010).

Table 2.4 shows the history of design discharges over the previous century and the beginning of this century. The first design discharge as we define it today was set in 1956 after the major floods of 1953 in the Netherlands. After twenty years it became clear that a design discharge of 18,000 $m^3s^{-1}$, with a safety level of 1/3,000 would be too costly and the measures would have a huge impact on cultural, historical and nature values. The Becht Commission, assigned by the national government, determined that the safety level could be adjusted to 1/1,250 and the design discharge could be decreased to 16,500 $m^3s^{-1}$. Another twenty years later the design discharge was decreased further to 15,000 $m^3s^{-1}$, because of a lot of public resistance against raising and broadening the dikes. This decrease in design discharge with the same safety level was consistent with a different statistical calculation method. The high waters of 1993 and 1995 placed safety back on the political agenda and the design discharge was raised again to 16,000 $m^3s^{-1}$ in 2001.

**Table 2.4.** Evolution of design discharges for the Dutch part of the Rhine basin (Kwadijk, Jeuken, & van Waveren)

| Year | Design discharge ($m^3s^{-1}$) | Safety level (recurrence interval in years) | Event |
|---|---|---|---|
| 1926 | Level of 1926 + 1m | - | Flooding 1926 |
| 1956 | 18,000 | 3,000 | Flooding 1953 |
| 1976 | 16,500 | 1,250 | Commission Becht |
| 1992 | 15,000 | 1,250 | Public resistance – Commission Boertien |
| 2001 | 16,000 | 1,250 | Flooding and evacuation 1995 |
| 2050[1] | 18,000 | 1,250 | Climate change – Second Delta Committee |



More extreme discharges are projected for the Rhine because of projected climate change, as explained in Section 2.3. Therefore, the design discharge has been under discussion again. On the basis of a study of Middelkoop et al. (2000) the Committee Water Management 21st century (WB21) has calculated an increase in design discharge of 5% per degree temperature rise. If a 'middle' scenario of the Royal Netherlands Meteorological Institute (KNMI) is taken, this translates into a design discharge of 18,000 $m^3s^{-1}$ for the Rhine. Spatial reservations are already made for the possibility of this discharge, although other measures taken at this moment are still based on a design discharge of 16,000 $m^3s^{-1}$. If a more extreme scenario is taken, the maximum design discharge could in theory be up to 22,000 $m^3s^{-1}$ for 2100. For this extreme scenario however, in practice the maximum discharge would be about 18,000 $m^3s^{-1}$, because of flooding upstream the Rhine basin. This, therefore means an upper limit of 18,000 $m^3s^{-1}$ to the discharge that can reach the Netherlands (Kabat, et al., 2009). The design discharge has been reason for a lot of discussion. The example of Table 2.4 illustrates the high impact of extreme events on the formulation and implementation of adaptation strategies. The determination of design discharges from statistical analyses of the measured peak discharges faces various problems. The estimation of the 1,250 year discharge event from statistical information in a discharge record of about 100 years involves a strong extrapolation, which is quite uncertain. Recent developments like the development of GRADE (Generator of Rainfall And Discharge Extremes) (De Wit & Buishand, 2007) have improved these extrapolations, but do not eliminate all uncertainty. The design discharge of 16,000 $m^3s^{-1}$ was included

[1] It is expected that between 2050 and 2100 the design discharge should be raised to 18,000 $m^3 s^{-1}$, in 2050 the measures taken to comply with this discharge should be finished.

in water safety legislation in the Netherlands in 2001, before research was done on flood safety in Germany in 2004. Without additional flood-protection measures in Germany an amount of 16,000 $m^3s^{-1}$ would not reach the Netherlands, as the Niederrhein would flood in Germany when the discharge is between 11,000 $m^3s^{-1}$ and 16,000 $m^3s^{-1}$, transboundary floods would occur at 14,000 $m^3s^{-1}$. This means that in case of large-scale flooding, the peak discharge at Lobith is reduced (Kroekenstoel & Lammersen, 2004). The cooperation and communication between the Netherlands and Germany definitely could have been better, for example, it could be unnecessary for the Netherlands to take measures for extreme discharges, if Germany is not doing this.

This case is a typical example of a 'predict-then-act' approach. Science and projections are taken as a starting point and the strategy is based on these projections. The strategy is vulnerable to uncertainty and surprises, as it relies on the scientific accuracy of the projection. If the projections are not accurate and the design discharge would be estimated wrongly, the damage could be huge. This example also shows that transboundary cooperation is essential for effective river basin management. The measures taken in the Netherlands should be adapted to measures in the other riparian countries, especially Germany and vice versa.

In the Netherlands the 'assess-risk-of-policy' approach has been applied for the area of water management using the concept of 'adaptation tipping points'. These 'tipping points' are reached if the current management strategy can no longer meet its objectives (Kwadijk et al., 2010). Only beyond the tipping points an additional adaptation strategy would be needed. The focus of this approach is on the resilience of the water system. The results of this study also have been input to the authoritative study on future adaptation options by the 2$^{nd}$ Delta Committee (Section 2.5). A number of case studies on sea level rise in the Netherlands which have explored this approach suggest that it may better match the way policy makers address questions than the 'predict-then-act' approach. The results have shown, for example, that for dikes along the tidal river area no major technical and financial adaptation tipping points will be reached any time soon, but that potential tipping points might arise on the social- and political level. Social acceptability, for example, of living behind giant dikes may decline (Kwadijk, et al., 2010). These experiences suggest that a 'assess-risk-of-policy' approach might be useful or at least complementary to the more commonly used 'predict-then-act' approach.

## 2.7 Discussion, conclusions and recommendations

In this paper we have identified factors that facilitate or constrain effective risk management with respect to climate adaptation in transnational river basins. The Rhine river basin was taken as a case study area, as it is a large international river basin with a history of droughts and floods. Three questions were addressed in particular: 'How are climate change uncertainties dealt with?, 'How does a (mis) match between information needs and knowledge availability across different geographic and administrative scales stimulate or constrain effective adaptation policy development?', and 'What is the effect of (lack of) transboundary cooperation on adaptation management?' A number of findings emerge:

*Scientific uncertainties provide opportunities for politically strategic water safety choices*.



A view on history shows that design discharges that have been established by water managers were at least informed by statistical analyses from scientific and technical advisors (see Section 2.6). So, the demand of knowledge by policymakers appears to be matched by the supply by scientists. However, the degree to which statistical calculations determine the design discharge can be debated, as over the last century a number of times the design discharge in the Netherlands changed not only as a result of new scientific insights or statistical methods, but also as result of extreme events, financial considerations or public opposition. Extreme events increase the level of public attention and sense of urgency and design discharges were increased to ease these public concerns. After some time remembrance of extreme events seem to fade away in the minds of people and the design discharges were lowered, requiring less costly measures. The political and societal discussion that follows extreme events offers a particular window of opportunity for scientists and scientific information to play a role in policy making (Arnell & Delaney, 2006). This is confirmed in a comparative study by Krysanova et al. (2010) where it was found that experts in different large river basins perceived a climate-related disaster amongst the most important drivers for development of adaptation strategies. But in turn, once the disaster is over, there is a tendency to return to the original situation instead of developing long-term policies (Christoplos, 2006). While after an extreme event re-active measures are taken, climate adaptation strategies, targeting future extreme events, ought to be pro-active. This proves to be very challenging as it is more difficult to create a sense of urgency for events that have not happened yet.

*Scientific support to water management strategies currently addresses uncertainties inadequately.*

Even if communication between scientists and policymakers in the area of water safety appears to have been quite satisfactory, particularly in The Netherlands, some questions can be asked. First of all, the question of selection of long-term climate scenarios is interesting. While initially a 'best guess' middle scenario was used, and even incorporated in legislation, later a more 'worst case' scenario was applied, although not in all cases. It is not completely clear if this was a decision by the relevant policymakers or by the scientific experts and what arguments were behind such decisions. At the same time, model calculations generally not only used one scenario, but also the output of only one global climate model, ignoring differences between model outcomes. It might be that for the coming decades the differences in terms of runoff projections between scenarios and climate models are relatively small and multiple model runs would be too costly, but this is not systematically discussed in the various papers and reports underpinning Dutch water policy.

In general, research on the human dimensions of climate change suggests that available information on climate change is often not perceived to be useful for policymakers, or is misused and contributes to undesired outcomes (Sarewitz & Pielke, 2007). In national and regional Dutch and German adaptation strategies uncertainties are mentioned in rather general terms, but it is not explicitly explained how governments could deal with these uncertainties. As a consequence, policy makers can use uncertainties strategically, as illustrated by the evolving choices on design discharges. At the same time, scientific output in the area of water management often does not provide the policy makers with clear information about the uncertainties and how to manage them. Three mismatches between the supply of knowledge and the demand of policy makers relate to spatial and time scaling, and to the scope and form of information provided. Most climate change information is available at long-term temporal scales and large spatial scales, but most management plans or adaptation strategies, from the Water Framework Directive to national plans, have their goals set for at the latest 2015, and usually focus on smaller scales (municipalities, regions, water basins). As to scope and form: often the information provided is too complex, and not expressed in terms directly relevant for the policy question that is supposed to be addressed. Policy makers mostly need information that is simple, and relevant for short-term local decisions. Of course, this is not easy and will not solve all the climate related policy challenges, as for example, environmental policy decision making tends to be highly politicized (Castree & MacMillan, 2001). Juntti et al (2009)discuss some of the challenges in the science policy interface. Firstly, they argue that the notion of validity of evidence would benefit from a more transparent treatment of the division into lay and expert knowledge in evidence generation. Secondly, the range of involved interests adds to the political struggle and finally it is argued that knowledge is only turned into 'evidence' when the political climate is ripe for a problem to be identified. Turnpenny et al. (2009) add to this discussion that technical uncertainties are often invoked as a reason for policy direction. These findings underline the arguments of this paper, the exchange of knowledge between science and policy is not straightforward and there are many factors that influence this process. For both scientists and policy makers it is important to be aware of these influences and to be clear about the choices and underlying assumptions that are made.

*Early experiences with 'assess-risk-of-policy' analysis of options (looking at the climate resilience of development plans rather than linking adaptation options to projected impacts) suggest that this method may be applied more widely.*

Because climate change is framed as a global problem, 'predict-then-act' scenario approaches are most commonly used in developing climate adaptation strategies and measures. This approach is strong in coping with statistical uncertainties and can profit from the large amount of available impact assessments. However, projections of future climate change also have uncertainties that cannot be quantified. Too much focus on climate change scenarios alone may lead to ineffective risk management. In the Netherlands, for example, the 'predict-then-act' approach may not lead to optimal decision making in the water sector in terms of robustness, flexibility and costs, if only one scenario and one model is chosen as a best or worst case estimate (Kwadijk, et al., 2010). The approach ignores governance questions. The 'assess-risk-of-policy' approach recognizes local interests and conditions, and offers possibilities to deal with uncertainties that cannot be quantified, by focusing on the resilience of the system. Research on this approach has only recently started, e.g. with the concept of adaptation tipping points. First results of this method show that it can offer policy makers a new, complementary tool for evaluating adaptation strategies that also addresses their non-climate priorities and maybe a different view on the urgency of adaptation to climate change. Therefore it would be interesting to do more research on 'assess-risk-of-policy' approaches and test these approaches more widely.



*Development and implementation of adaptation options derived from integrated analysis at the full river basin level rather than within the boundaries of the riparian countries can offer new opportunities but will also meet with many practical challenges.*

The history of water management in the Rhine basin has shown that international cooperation can be successful. Agreements on water pollution of the Rhine have led to a successful improvement of water quality. A comparative study of Ma et al. (2008) showed that the 1998 Rhine Convention is the best transboundary water treaty for enforcement, capability and treaty implementation. This can be an example for other transboundary cooperation, e.g. to address climate change adaptation in the most cost effective manner. Taking a closer look at regional policy practices along member states' borders, however, suggests that cooperation is often still viewed as problematic. So, while 'Europe' is striving for a borderless river basin management, harsh realities reflected in regional practices do not always meet these expectations (Wiering, Verwijmeren, Lulofs, & Feld, 2010). International cooperation in river basins with respect to climate change adaptation is very important, as measures in one country could have negative effects in another or country-by-country measures could be less effective or more expensive than measures optimized over the full river basin. In the case of the Rhine, the latter can be illustrated by the current understanding that the design discharge of 16,000 $m^3s^{-1}$ was included in Dutch legislation before research was done on the impacts of floods on high water in Germany. Results of this research showed for example that an extreme discharge of 18,700 $m^3s^{-1}$ at Lobith would be reduced to 15,500 $m^3s^{-1}$ at Lobith because of flooding in Germany (Lammersen, 2004). Of course, this may change as the climate changes and further protective measures are taken throughout the river basin. This example shows the potential importance of enhanced cooperation, especially since the projection of climate change impacts suggests that more adaptation measures will be necessary in the future. If the difficulties caused by different institutional arrangements and cultural differences were to be explicitly recognized and systematically addressed, more effective transnational collaboration would be possible. However, to reach this goal, political will from the riparian countries is essential. Until now this will and the means to put this will into action is not clearly expressed in the governmental documents on climate adaptation that we have analysed.

*Knowledge gaps.*

We identified a number of knowledge gaps that require research attention. While much is known about technical aspects of measures, institutional barriers for pro-active adaptation are less well understood. Research has addressed the problem of climate change uncertainties in climate and impacts models separately, but the consequences of the propagation through the various analytical steps for risk management is poorly understood. The discussion on climate-related uncertainties is mainly science-driven, and more attention is required on how policymakers deal with them: the communication of uncertainties should be fit for purpose. The implementation of adaptation measures depends on interactions of different governance levels, more research is required to understand how this affects the formulation and actual implementation of adaptation strategies. So far, the most common approach to impacts and adaptation assessment is the projected climate impacts-driven 'predict-then-act' approach more attention is required to alternative, or complementary 'assess-risk-of-policy' approaches in support of the enhancement of climate resilience. Different countries in transnational river basins use different methods and climate impact information. Research to better understand the constraints and opportunities of transboundary cooperation with respect to climate change impacts and adaptation assessment in international river basins would be useful. This paper is based on literature review and informal contacts, for a better understanding of the details of how past decisions were made, more systematic research supported by well-structured interviews would be a useful complement to the literature review. While some of these suggestions are likely to be addressed in new national research programmes, such as Knowledge for Climate in the Netherlands and Klimzug in Germany, stronger and sustained international research collaboration would strengthen the scientific quality and policy-relevance of the projects.

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# Chapter 3

# Future changes in extreme precipitation in the Rhine basin based on global and regional climate model simulations

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# Abstract

Probability estimates of the future change of extreme precipitation events are usually based on a limited number of available global climate model (GCM) or regional climate model (RCM) simulations. Since floods are related to heavy precipitation events, this restricts the assessment of flood risks. In this study a relatively simple method has been developed to get a better description of the range of changes in extreme precipitation events. Five bias-corrected RCM simulations of the 1961–2100 climate for a single greenhouse gas emission scenario (A1B SRES) were available for the Rhine basin. To increase the size of this five-member RCM ensemble, 13 additional GCM simulations were analysed. The climate responses of the GCMs are used to modify an observed (1961–1995) precipitation time series with an advanced delta change approach. Changes in the temporal means and variability are taken into account. It is found that the range of future change of extreme precipitation across the five-member RCM ensemble is similar to results from the 13-member GCM ensemble. For the RCM ensemble, the time series modification procedure also results in a similar climate response compared to the signal deduced from the direct model simulations. The changes from the individual RCM simulations, however, systematically differ from those of the driving GCMs, especially for long return periods.

## 3.1 Introduction

Heavy precipitation events are of importance since they are a major cause of floods, which can have large impacts on society. Based on a wide range of observational and global climate model (GCM) and regional climate model (RCM) studies, changes in greenhouse gas concentrations are expected to affect the frequency and magnitude of extreme precipitation. These studies show an intensification of precipitation extremes over most of Europe (Beniston, et al., 2007; Buonomo, Jones, Huntingford, & Hannaford, 2007; Fowler & Ekström, 2009; Frei, Schöll, Fukutome, Schmidli, & Vidale, 2006; Hanel & Buishand, 2011; Kyselý & Beranová, 2009; Kyselý, Gaál, Beranová, & Plavcová, 2011; Nikulin, Kjellström, Hansson, Strandberg, & Ullerstig, 2011). The projections of changes in the precipitation extremes are sensitive to the choice of RCMs, the driving GCM and the emission scenario. Credible high-resolution climate scenarios for impact studies require an ensemble of RCM simulations driven by multiple GCMs (Bernstein et al., 2007; Fowler, et al., 2007). Ideally, such ensembles should represent the full range of natural variability and model uncertainty. In practice, however, they are assembled on an opportunity basis, and often the size of the ensembles is restricted by limited resources (Kendon, Jones, Kjellström, & Murphy, 2010).



For this study the bias corrected output of five RCM simulations was used through the Rheinblick2050 project (Görgen, et al., 2010), where a comprehensive ensemble of hydrological simulations driven by the output of RCMs was used to analyse future changes in the Rhine discharge regime. The five RCMs were driven by GCMs that were all forced with the A1B SRES emission scenario. It is of interest to assess to what degree the results based on such a small sample size describe the uncertainty associated with the model error and natural variability. RCMs can resolve small scale features, but can still contain large biases, partly inherited from the driving GCMs. The five-member RCM ensemble from the Rheinblick2050 project was extended with an ensemble of 13 GCM simulations to get a better description of the uncertainty induced by the GCM ensemble. Several studies have indicated that this uncertainty exceeds the uncertainty arising from the choice of downscaling techniques and emission scenarios (Graham, et al., 2007; Menzel, et al., 2006; Prudhomme & Davies, 2009; Rowell, 2006; Wilby & Harris, 2006). Also the GCM ensemble was driven by the A1B emission scenario. Since high resolution RCM simulations from all these 13 GCM simulations were not available we followed a pragmatic approach by post-processing the GCM outputs, using ‘change factors’ (Arnell & Reynard, 1996; Diaz-Nieto & Wilby, 2005), also referred to as the *delta change approach* (Lenderink, Buishand, et al., 2007; Prudhomme, Reynard, & Crooks, 2002; Te Linde, et al., 2010).

Because safety levels along the Rhine are high, this study focused on changes in very rare extreme events. For flood protection in the Netherlands a design discharge is used that is exceeded, on average, only once in 1,250 year. To determine this design discharge, the distribution of the relatively short observed discharge series needs to be statistically extrapolated to the required exceedance probability. Extrapolation of the distributions fitted to the observed flood peaks leads to large uncertainties (Klemeš, 2000a, 2000b). Alternatively, a weather generator (Buishand & Brandsma, 2001) has been used to create long climate time series by resampling the historical data. To be able to analyse extreme discharge the weather generator can be coupled to a rainfall-runoff model for the Rhine, but this step was not considered in the present study.

This study explores the possibility to combine the future changes in extreme precipitation from an RCM ensemble with the future changes in a GCM ensemble. A new delta change method for precipitation is introduced that allows changes in the extremes to be different from changes in the mean. The range of future changes in extreme multi-day precipitation of the RCM ensemble is compared with the range of the GCM ensemble. A comparison is also made between the signal of the individual RCM simulations and the signal of the driving GCMs. Furthermore, the delta change approach is validated against the use of bias corrected RCM output.

## 3.2 Study area and data

### 3.2.1 The Rhine basin

The river Rhine originates in the Swiss Alps as a mountain river, fed by glacier water, snowmelt and rainfall. From Switzerland it flows through Germany and the Netherlands into the North Sea. The Rhine basin has an area of about 185,000 km$^2$, and the river has a length of 1,238.8 km, making it the longest river in Western Europe. The annual mean discharge (1901-2000) at Lobith, where the Rhine enters the Netherlands, is 2,200 m$^3$s$^{-1}$. The estimated 1,250-year return level (the discharge that is exceeded, on average, once in 1,250 year) at this site is 16,000 m$^3$s$^{-1}$.

The climate of the Rhine basin is determined by its location in a Western European zone of temperate climatic conditions with frequent synoptic weather changes. From the northwest to the east and southeast, the maritime climate gradually changes into a more continental climate. Precipitation occurs all year round; mean annual precipitation ranges from about 500 mm in parts of the Rhine valley to 3,000 mm in some parts of the Alpine region. Spatially averaged annual precipitation sums between 1901 and 2000 (Belz et al., 2007) point towards a slight increase in different sub-regions against a fairly uniform background decadal-scale variability. The increase of precipitation is more pronounced during the hydrological winter (November-April).

### 3.2.2 RCM and GCM data set

In Table 3.1 an overview is given of RCM and GCM simulations of which the precipitation output is considered in this study. In the Rheinblick2050 project (Görgen, et al., 2010) the RCM simulations were used as input of the hydrological HBV (Hydrologiska Byråns Vattenbalansavdelning) model (Bergström & Forsman, 1973) for the Rhine basin to study the impact of climate change on the discharge in this river basin. We have selected five out of the six RCM simulations used in the Rhineblick2050 project; the ARPEGE-HIRHAM simulation was left out, because the complex reduced grid structure of the ARPEGE model did not allow a straightforward interpolation to a common grid. With the exception of the REMO_10 simulation, the RCM data were obtained from the archive of the ENSEMBLES project (Van der Linden & Mitchell, 2009). Model-specific bias corrections (Görgen, et al., 2010) were derived by comparing the RCM control simulations with a high resolution observed precipitation data set (see Section 3.2.3).

The additional GCM data were obtained from the Coupled Model Intercomparison Project Phase 3 (CMIP3) archive (Meehl, Covey, Delworth, & Latif, 2007). All GCM simulations used are driven by the A1B emission scenario. The GCM output was interpolated to a common 2° longitude by 2.5° latitude grid. The Rhine basin is covered by eight grid cells (see Figure 3.1). For all GCMs a control run period of 35 year (1961-1995) and a scenario run period of 20 year (2081-2100) were used. The choices for these periods were based on data availability. The main problem of unequal sizes is that it may lead to biases in the estimation of parameters used in the delta method. Therefore, changes were also considered with respect to the 20-year control periods 1961-1980 and 1976-1995. The averages of these changes did not differ much from the changes with respect to the 35 year control run period (1961-1995).



**Table 3.1.** GCM and RCM simulations used in this study. Note that two different transient simulations with the ECHAM5 model (r1 and r3, which refer to runs with different initial conditions) were used as RCM boundary conditions; two RCMs are forced by ECHAM5r3.

| GCM | RCM | GCM References | RCM References |
|---|---|---|---|
| CGCM3.1T63 | | Flato (2005) | |
| CNRM-CM3 | | Salas-Mélia et al. (2005) | |
| CSIRO-Mk3.0 | | Gordon et al. (2002) | |
| ECHAM5r1 | REMO_10 | Roeckner et al. (2003) | Jacob (2001) |
| ECHAM5r3 | RACMO | | Lenderink (2003) |
| | REMO | | Jacob (2001) |
| GFDL-CM2.0 | | Delworth et al. (2006) | |
| GFDL-CM2.1 | | | |
| HADCM3Q0 | CLM | Gordon et al. (2000) | Steppeler et al. (2003) |
| HADCM3Q3 | HADRM3Q3 | | Jones (2004) |
| IPSL-CM4 | | Marti et al. (2006) | |
| MIROC3.2 hires | | Hasumi and Emori (2004) | |
| MIUB | | Min et al. (2005) | |
| MRI-CGCM2.3.2 | | Yukimoto et al. (2006) | |

### 3.2.3 Observations

Observations of precipitation for the Rhine basin were available from the International Commission for the Hydrology of the Rhine basin (CHR). The so-called CHR-OBS data set (De Wit & Buishand, 2007) contains area-averaged daily precipitation for 134 sub-basins of the Rhine basin that were defined for hydrological simulations with the HBV model. The CHR-OBS data cover the period 1961-1995. A newer and longer precipitation data set has become available recently (Photiadou, Weerts, & Van den Hurk, 2011) but this data set could not be used in this study because the bias corrections of the RCM output in the Rheinblick2050 project were based on the CHR-OBS data set. In a companion study, the HBV model was used to analyse and interpret the results described in this paper in terms of changes of flood risk (Ward et al., 2013).

## 3.3 Methodology

### 3.3.1 Time series transformation

An advanced delta method was used to transform the CHR observations into a time series that is representative of future conditions consistent with the GCM climate change signal. The delta method makes use of 'change factors', and is therefore also referred to as the *delta change approach*. The simplest form of the delta method (sometimes referred to as the 'classical delta method') only considers changes in the mean. The change in the mean may vary seasonally throughout the year or spatially. When coupling with impact models is required (e.g. with a hydrological model), delta methods have a practical advantage that an observed reference time series at the temporal and spatial scale of interest can be used to represent the current climate. The assumption that one has to make is that changes at the (large) scale of the climate model (GCM) can be directly applied to the (local) scale of the time series.

In this study, a more advanced delta method was used, that not only takes changes in the mean into account but also the changes in the extremes. Again, these changes can vary seasonally and spatially. Rather than a proportional adjustment of observed precipitation, the following non-linear transformation was applied to the bulk of the data (see also Figure 3.1 for a graphical summary of the complete procedure):

$$P^* = aP^b \qquad (3.1)$$

where $P$ and $P^*$ represent the observed and future precipitation, respectively, and $a$ and $b$ are the transformation coefficients ($a$, $b$ >0). Shabalova et al. (2003) showed that this relation between $P^*$ and $P$ arises if the parameters of a fitted Weibull distribution are perturbed. Leander and Buishand (2007) used this type of transformation to correct for bias in RCM simulations for the Meuse basin; i.e., Eq. (3.1) was applied to RCM output rather than observed precipitation as in the present study. In addition, Eq. (3.1) was modified for large $P$ and the transformation coefficients were smoothed in this study (see below).

Several studies have indicated that extreme discharges in the lower part of the Rhine generally result from extreme multi-day precipitation amounts in the river basin. For instance, during the December 1993 and January 1995 floods precipitation was extreme over a 10-day period (Disse & Engel, 2001; Ulbrich & Fink, 1995). Therefore, the future change in (extreme) multi-day precipitation is more relevant than the change in (extreme) daily precipitation. In this study Eq. (3.1) was applied to non-overlapping 5-day sums (73 5-day periods in a calendar year of 365 days). The 5-day time step recognizes the relevance of multi-day precipitation sums, but yet is small enough to be linked with daily precipitation as well.

The coefficients $a$ and $b$ were derived from the 60% quantile ($P_{60}$) and the 90% quantile ($P_{90}$) of the 5-day precipitation sums and the (future) changes therein. Sample quantiles based on the ordered non-overlapping 5-day precipitation amounts were used as estimates of $P_{60}$ and $P_{90}$. $P_{60}$ was considered because this quantile is generally closer to the mean than the median value ($P_{50}$) owing to the positively skewed probability distribution of the 5-day precipitation amounts. $P_{90}$ (which is exceeded on average once in ten 5-day periods) is in the range of the seasonal maximum 5-day precipitation amounts (see Supplementary information A1). Since the transformation given by Eq. (3.1) represents a monotonic increase, the quantiles of the transformed 5-day precipitation sums are simply obtained by applying the same transformation to the quantiles of the observed 5-day precipitation:

3

$$P_{60}^{*} = a(P_{60})^{b} \tag{3.2}$$

$$P_{90}^{*} = a\,(P_{90})^{b} \tag{3.3}$$

From these two equations, first $b$ was solved by eliminating $a$ (Leander and Buishand, 2007):

$$b = \frac{log(P_{90}^{*}/P_{60}^{*})}{log(P_{90}/P_{60})} \tag{3.4}$$

Once $b$ was determined, $a$ was obtained by substituting $b$ into Eq. (3.2):

$$a = P_{60}^{*}/(P_{60})^{b} \tag{3.5}$$

If there is no bias in the 60% quantile $P_{60}^{C}$ and the 90% quantile $P_{90}^{C}$ in the GCM control simulation compared to the observations, the quantiles $P_{60}^{C}$ and $P_{90}^{C}$ can be substituted for $P_{60}$ and $P_{90}$ in Eqs. (3.4) and (3.5), and the quantiles $P_{60}^{F}$ and $P_{90}^{F}$ in the future climate for $P_{60}^{*}$and $P_{90}^{*}$. However, if $P_{60}$ and $P_{90}$ are biased, this method results in a transformation that does not reproduce the relative changes in these quantiles. In order to ensure that the relative changes of $P_{60}$ and $P_{90}$ in the transformed series correspond to the relative changes of these quantiles in the GCM simulation, the following bias-correction factors were introduced:

$$g_{1=} P_{60}^{\mathrm{O}}/P_{60}^{\mathrm{C}} \tag{3.6}$$

$$g_2 = P_{90}^{\mathrm{O}}/P_{90}^{\mathrm{C}} \tag{3.7}$$

where the superscript C again refers to the GCM control climate and O refers to observed (reference) data. These corrections were applied to $P_{60}{}^{\mathrm{C}}$ and $P_{90}{}^{\mathrm{C}}$ as well as $P_{60}{}^{\mathrm{F}}$ and $P_{90}{}^{\mathrm{F}}$. The coefficients $a$ and $b$ then become:

$$b = \frac{\log\{g_2 \cdot P_{90}^{\mathrm{F}}/(g_1 \cdot P_{60}^{\mathrm{F}})\}}{\log\{g_2 \cdot P_{90}^{\mathrm{C}}/(g_1 \cdot P_{60}^{\mathrm{C}})\}} \tag{3.8}$$

$$a = P_{60}^{\mathrm{F}}/\left(P_{60}^{\mathrm{C}}\right)^b \cdot\ g_1^{1-b} \tag{3.9}$$

Note that the classical delta change method is obtained by assuming that the GCM responses in the 60 and 90% quantiles are equal:

$$P_{90}^{\mathrm{F}}/P_{90}^{\mathrm{C}} = P_{60}^{\mathrm{F}}/P_{60}^{\mathrm{C}}$$

leading to $b$ = 1 and $a = P_{60}{}^{\mathrm{F}}/P_{60}{}^{\mathrm{C}}$, and therefore Eq.(3.1) reduces to $P^* = aP$.

**Transformation for large *P***

Equation (3.1) was applied to the observed values for which $P \leq P_{90}{}^{\mathrm{O}}$ . For larger $P$ this equation is not flexible enough to reproduce the changes in the extremes adequately. This could be improved by separately addressing the change in the excesses, $E = P - P_{90}$, i.e. the events exceeding $P_{90}$. The mean excesses for the control and future period were defined as :

$$\bar{E}^{\mathrm{C}} = \frac{\sum E^{\mathrm{C}}}{n^{\mathrm{C}}} \quad \text{and} \quad \bar{E}^{\mathrm{F}} = \frac{\sum E^{\mathrm{F}}}{n^{\mathrm{F}}} \tag{3.10}$$

where $n^{\mathrm{C}}$ and $n^{\mathrm{F}}$ are the numbers of 5-day periods in which the 90% quantile is exceeded in the control and future run, respectively. The size of the mean excess is closely related to the slope of an extreme-value plot of the seasonal maximum 5-day precipitation amounts (see Supplementary information A1).

To ensure that the transformation reproduces the change in the mean excess, Eq. (3.1) was modified as:

$$P^* = \bar{E}^{\mathrm{F}}/\bar{E}^{\mathrm{C}} \cdot \left(P - P_{90}^{\mathrm{O}}\right) + a\left(P_{90}^{\mathrm{O}}\right)^b \qquad \text{for } P > P_{90}{}^{\mathrm{O}} \tag{3.11}$$

Effectively the excess scales linearly with the factor $\bar{E}^{\mathrm{F}}/\bar{E}^{\mathrm{C}}$. The use of Eq. (3.11) also avoids unrealistically high precipitation amounts, which may occasionally occur when Eq. (3.1) is used when $P > P_{90}{}^{\mathrm{O}}$ and $b > 1$.

In principle the coefficients $a$ and $b$ and the change in the mean excesses $\overline{E}^F/\overline{E}^C$ may vary seasonally and spatially. To reduce sampling variability in the transformation coefficients, we chose to use smoothed, but distinct values of $a$, $b$ and $\overline{E}^F/\overline{E}^C$ for each calendar month. First, the quantiles $P_{60}$ and $P_{90}$ were estimated for each calendar month using six 5-day periods for the calendar months January to November and seven 5-day periods for December. These monthly estimates of $P_{60}$ and $P_{90}$ were subsequently smoothed over time by using a 3-month moving average with weights ¼, ½ and ¼. The mean excesses $\overline{E}^C$ and $\overline{E}^F$ were smoothed over time similarly. The temporally smoothed estimates of $P_{60}$ and $P_{90}$ were used in Eq. (3.8) to obtain a temporally smoothed value of $b$ for each calendar month and for each grid cell in the basin. To reduce sampling variability further, the median value of $b$ over the eight grid cells for each calendar month was used for all grid cells in the basin. Analogously, the median of $\overline{E}^F/\overline{E}^C$ over the eight grid cells was taken for each calendar month. The coefficient $a$ finally varies spatially (a distinct value for each grid cell in the basin) and was obtained by using the temporally smoothed $P_{60}$ and the spatially uniform value of $b$ in Eq. (3.9).



Here daily precipitation amounts for the 134 HBV sub-basins in the Rhine basin for the period 1961-1995 were used as the baseline time series. Eqs. (3.1) and (3.11), however, apply to the area-average precipitation over a GCM grid cell. The precipitation amounts for the HBV sub-basins were therefore aggregated to grid cell values by taking an area-weighted average of all sub-basins lying in the respective grid cell. After the transformation using Eqs. (3.1) and (3.11), the final step involved the disaggregation of the transformed 5-day precipitation values at the GCM grid cell into daily precipitation at the sub basin scale. For this a change factor $R$ was defined for each grid cell and 5-day period as:

$$R = P^*/\ P \qquad (3.12)$$

Each daily observation in a sub-basin allocated to a given GCM grid cell was transformed according to the corresponding value of $R$. Thus, the daily observations in a 5-day period obtained the same relative change. The method ensures that the change in the temporally and spatially aggregated daily precipitation of the sub-basins corresponds to the change in the 5-day precipitation over the grid cell. The non-linear nature of Eqs. (3.1) and (3.11) generally results in different change factors for days in distinct 5-day intervals. The result is a future time series of daily precipitation on sub-basin level.

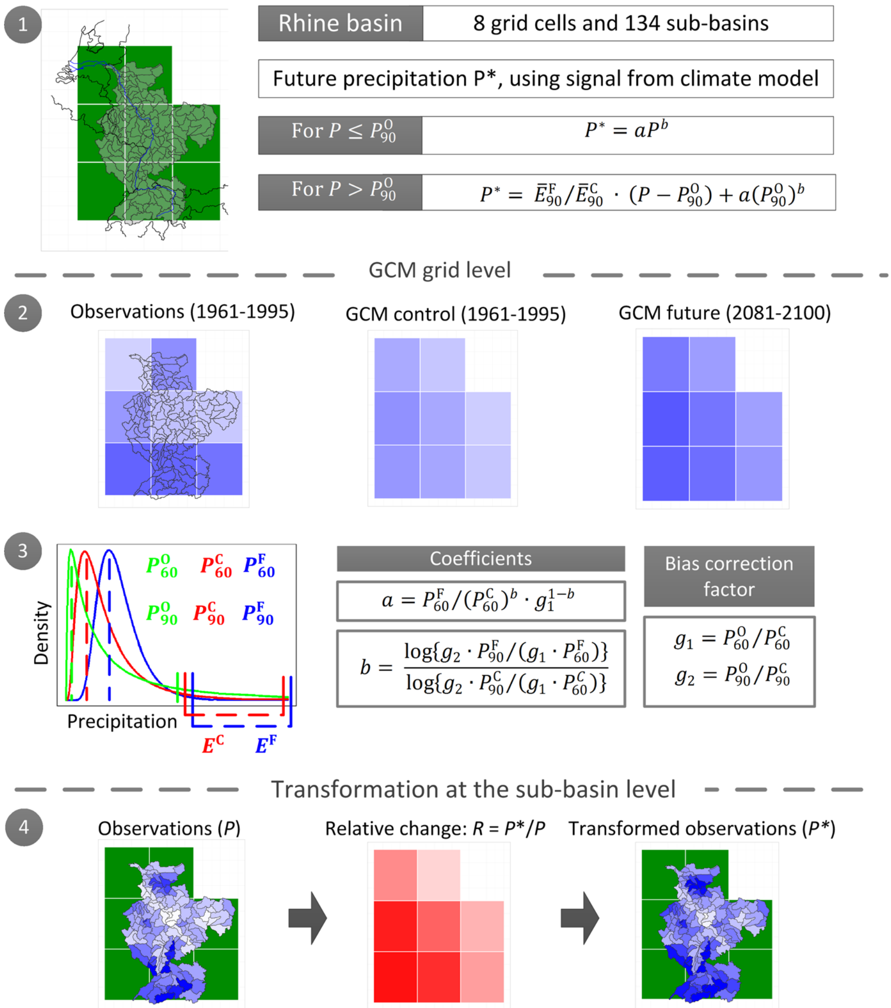


**Figure3.1.** Overview of the methodology. Panel 1 shows the Rhine basin, divided in 8 (GCM) grid cells and 134 sub-basins. Panel 2 shows the mean precipitation over a 5-day period in each grid cell for the observations and the control and future GCM simulation, all on grid cell level. The observations were upscaled to grid cell level by taking a weighted average over the sub-basins. In panel 3, the probability density of 5-day precipitation is shown, with the 60% ($P_{60}$) and the 90% ($P_{90}$) quantiles (for the observations as well as for GCM control and future simulations). Also the excess (the amount of precipitation > the 90% quantile) is shown for the control and the future model run. Panel 4 displays the transformation. The daily observations in each sub-basin were multiplied by the change factor $R$, which was obtained from the observed ($P$) and transformed ($P^*$) 5-day precipitation amount and depends on the coefficients $a$ and $b$ and for $P$ > $P_{90}$ also on $\bar{E}^{F}/\bar{E}^{C}$. For each sub-basin the daily precipitation was transformed using the GCM signal from the grid cell that contains most of its surface area.

### 3.3.2 Exploring the sensitivity of choices

In the process of developing and applying the advanced delta change method a number of choices were made. These choices influence the changes in the return levels of extreme precipitation. In this section, the sensitivity of the results to some of these choices is discussed.

Temporal and spatial smoothing was applied to reduce the influence of sampling noise on the estimated climate change signal. Spatial variation of $b$ and $\overline{E}^{F}/\overline{E}^{C}$ was ignored. The need for temporal and spatial smoothing is shown in Figure 3.2 for two GCM simulations. The changes from the model output were used to transform the observed data, both with and without temporally and spatially smoothed coefficients in Eqs. (3.1) and (3.11). The figure gives the relative changes of the return levels of 10-day precipitation for the winter-half year (October -March) as a function of return period. The winter half-year is the main season of interest for high river discharge in the lower part of the Rhine basin.



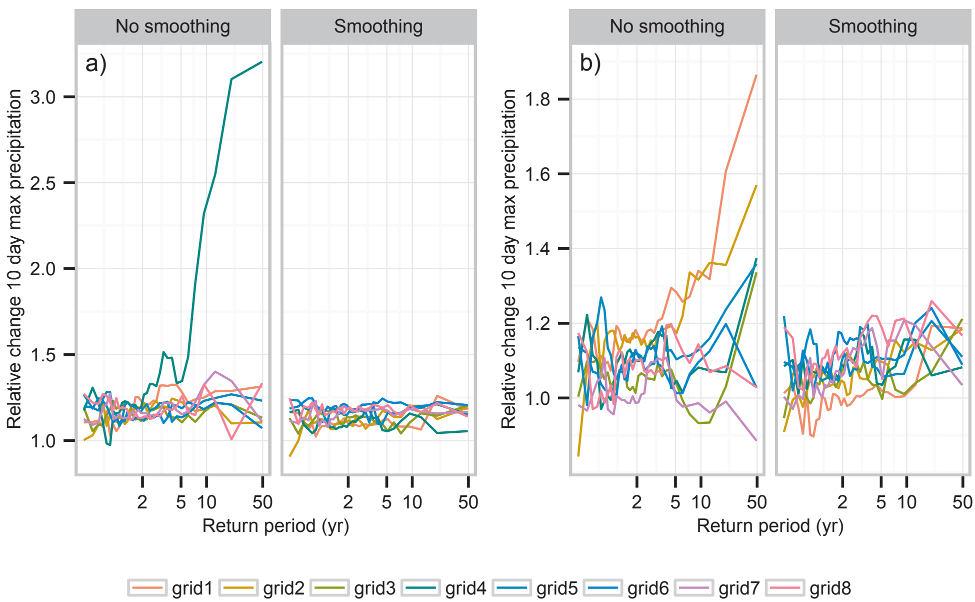


**Figure 3.2.** Relative changes of the return levels of 10-day precipitation in the winter half-year (October – March) for each of the eight GCM grid cells covering the Rhine basin. Panel (a): results for the CGCM3.1T63 simulation; panel (b): results for the ECHAM5r1 simulation. Within both panels, the left part shows the results for no temporal and spatial smoothing and the right part shows the results with smoothing. Note the difference in plotting scale for the CGCM3.1T63 and ECHAM5r1 results.

The changes are shown for each grid cell of the Rhine basin separately. Similar figures were made for all other GCM simulations. For the transformed data based on the CGCM3.1T63 simulation (panel a of Figure 3.2) an unrealistically large increase for return periods > 10 year was found at grid cell 4 when no smoothing was applied. A physically plausible explanation is lacking for the huge precipitation amounts resulting from the changes of a factor of 3 or more in the right tail of the distribution.

The results for the ECHAM5r1 simulation (panel b) are characteristic for most other GCM simulations. The spread of the relative changes strongly increases with increasing return period when temporal and spatial smoothing were not applied. Smoothing also improved the correspondence between the changes in the mean precipitation and the mean 10-day maximum basin-average precipitation from the transformed time series and the changes in these properties from the climate model output (not shown).

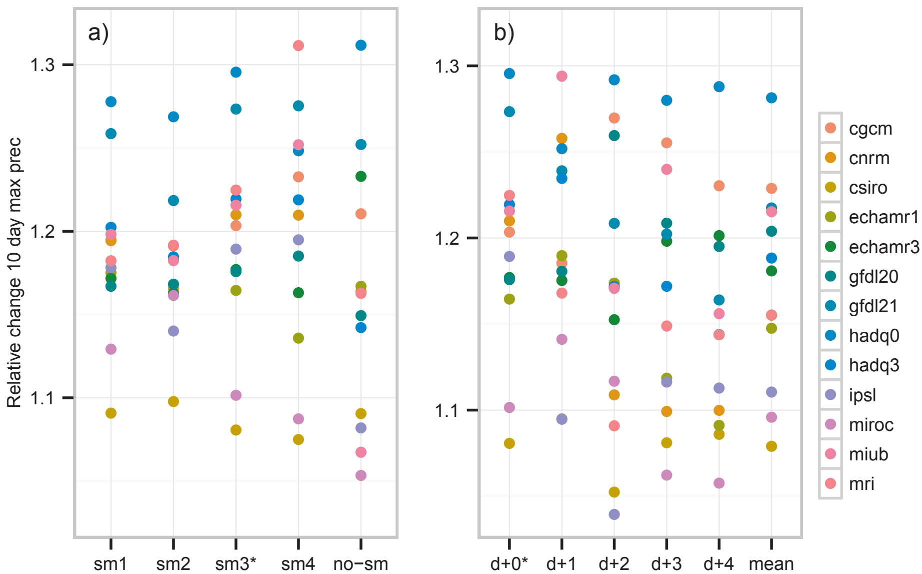


**Figure 3.3.** Relative changes of the 10-year return level of the 10-day basin-average precipitation in the winter half-year (October – March) for each GCM. Panel (a) shows the effect of different choices for temporal smoothing: two 5-month moving averages with weights 1/16, 1/8, 3/8, 1/8, 1/16 (sm1) and 1/8,1/4,1/4,1/4,1/8 (sm2), two 3-month moving averages with weights 1/4,1/2,1/4 (sm3) and 1/8, 3/4, 1/8 (sm4) and no temporal smoothing (no-sm). Panel (b) shows the effect of shifting the 5-day period. Mean indicates the mean of the relative changes of the 5 different shifts for each GCM simulation. The asterisk indicates the 5-day period (a) or the type of smoothing (b) used in this study.

The effect of different choices for temporal smoothing on the relative changes of the 10-year return level of the 10-day basin-average precipitation in the winter half-year is shown in Figure 3.3. The range of these changes is similar for the first three smoothers, but grows when less or no smoothing is applied. It further turned out that the degree of spatial smoothing has little effect on the relative changes in the 10-year return level of the 10-day basin average precipitation.

The coefficients and quantiles (described in Section 3.3.1) were based on non-overlapping 5-day precipitation sums. The sensitivity of shifting the 5-day period 1 to 4 days on the relative changes of the 10-year return level of 10-day basin-average precipitation is also shown in Figure 3.3. A shift of the 5-day period has a marked effect for some climate model simulations; the overall effect on the ensemble range is small.



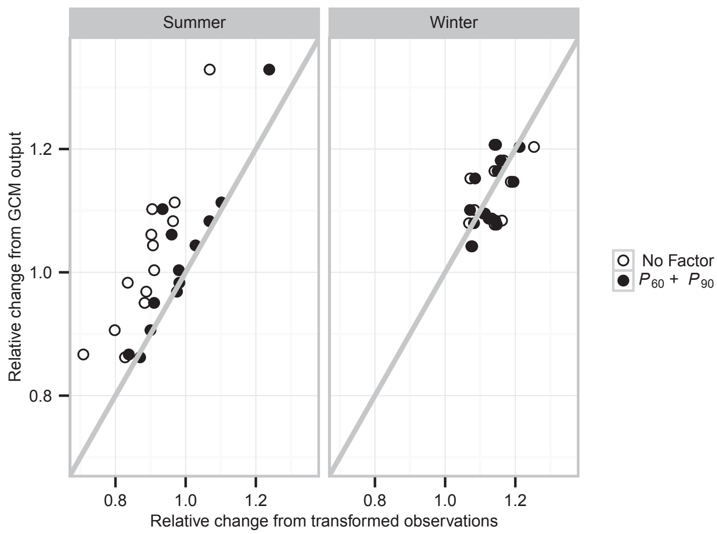


**Figure 3.4.** Comparison of the relative change (future versus present day) of the mean 10-day maximum basin-average precipitation derived directly from the raw GCM model output versus the change obtained from the transformation procedure for summer (left panel) and winter (right panel). Relative changes from the transformed observations are shown for no bias correction (No Factor) and for bias correction on $P_{60}$ and $P_{90}$ ($P_{60}$+$P_{90}$). The grey line represents optimal correspondence (i.e. the 1:1 line).

The sensitivity to the bias correction of the 60 and 90% quantiles of the 5-day precipitation sums in the GCM simulations was tested by comparing the relative changes in the mean 10-day maximum basin-average precipitation in the raw GCM model output to the changes in the transformed data taking either $g_1$ and $g_2$ as specified using Eqs. (3.6) and (3.7) or $g_1 = g_2 = 1$, i.e without bias correction. Figure 3.4 shows the results for the summer half-year (April - September) and the winter half-year (October-March). For summer the bias correction on both $P_{60}$ and $P_{90}$ leads to the best correspondence between the transformed time series and the direct GCM simulations. For winter the bias corrections only play a minor role.

### 3.3.3 Resampling

To estimate quantiles of the distributions of extreme precipitation amounts, a 3,000-year synthetic sequence of daily precipitation was available for each HBV sub-basin from the work of Beersma (2002). Daily precipitation was generated with daily temperature using nearest neighbour resampling from the 35-year record of historical observations. The 3,000-year precipitation series were transformed to future time series with the advanced delta method described in Section 3.3.1.

The method of time-series resampling of meteorological variables in the Rhine basin applied in this study, has been originally developed as part of a new methodology to determine the design discharge for flood protection in the Netherlands (Beersma & Buishand, 2003; Wójcik, Beersma, & Buishand, 2000). Leander and Buishand (2007) and Leander et al. (2008) applied the same methodology for the first time to RCM data, but for the Meuse basin. Recently it has also been applied for the Rhine basin using time series from the RACMO RCM driven by the ECHAM5 GCM (Te Linde, et al., 2010) and from an ensemble of RCMs in the Rheinblick2050 project (Görgen, et al., 2010). The resampled RCM data from the Rheinblick2050 project were made available for the present study.

Nearest-neighbour resampling was used to reproduce temporal correlation and to preserve the dependence between daily precipitation and temperature (Rajagopalan & Lall, 1999). In the multi-site application for the Rhine basin, daily precipitation and temperature were sampled simultaneously with replacement from the historical data to preserve their mutual dependencies. Summary statistics of the daily precipitation and temperature fields were needed in this application to avoid problems with the high dimensional data space . In each simulation step, the 10 nearest neighbours of the last generated day in terms of these summary statistics are searched for in the historical data. Details about the sensitivity of the autocorrelation and the simulated extremes to the summary statistics used and parameters in the resampling procedure can be found in Buishand and Brandsma (2001).

To reduce the effect of seasonal variation, the search for nearest neighbours was restricted to days within a moving window of 61 days, centred on the calendar day of interest (Beersma, 2002; Wójcik, et al., 2000). Daily precipitation was standardized by dividing by the mean wet-day precipitation amount of the calendar day of interest.

## 3.4 Results

### 3.4.1 Change in mean, standard deviation and quantiles

Table 3.2 presents the changes in the 60 and 90% quantiles and the change in the mean excess after the transformation defined by Eqs. (3.1) and (3.11) has been applied to the 5-day sums of the observed precipitation series for all model simulations presented in Table 3.1. From Table 3.2 it can be seen that for the GCM simulations the changes in the 90% quantile and especially the mean excess ($\overline{E}$) are generally stronger than the changes in the 60% quantile, which supports the use of a non-linear delta method. In particular for GFDL2.1-CM2.1 and IPSL-CM4 the change in the mean excess largely exceeds the change in the 60 and 90% quantiles. In contrast, the relative changes in $P_{60}$, $P_{90}$ and mean excess are very similar for the RCM simulations. Also, the relative changes for the RCM output processed with the delta method are similar to those for the bias corrected RCM output from the Rheinblick2050 project. However, the relative changes for the RCMs generally differ from the relative changes of their driving GCM. The RCMs exhibit a smaller change in the mean excess ($\overline{E}$) than their driving GCM, except those forced by ECHAM5r3.

3

**Table 3.2.** Relative changes in the 60% quantile ($P_{60}$), the 90% quantile ($P_{90}$) and mean excess ($\overline{E}$) after a transformation of the 5-day precipitation sums of the observed precipitation based on the simulated changes between 1961-1995 and 2081-2100 of a GCM or RCM. The changes are basin-average relative changes for the winter half-year (October – March). The changes between the observed and transformed data were obtained by taking the median of the relative changes of the temporally smoothed estimates for each calendar month over the eight grid cells at the common GCM resolution and averaging these medians for the winter half-year. For the RCMs, the transformation was applied after the RCM output was aggregated to the GCM grid resolution. The results in the columns headed, $P_{60}^{\mathrm{DIR}}$, $P_{90}^{\mathrm{DIR}}$ and $\overline{E}^{\mathrm{DIR}}$ refer to the direct use of bias corrected RCM output from the Rhineblick2050 project. For the latter, the relative changes were based on the differences between the RCM control and RCM future period.

| GCM/RCM | $P_{60}$ | $P_{90}$ | $\overline{E}$ | $P_{60}^{\mathrm{DIR}}$ | $P_{90}^{\mathrm{DIR}}$ | $\overline{E}^{\mathrm{DIR}}$ |
|---|---|---|---|---|---|---|
| CGCM3.1T63 | 1.10 | 1.11 | 1.22 | | | |
| CNRM-CM3 | 0.97 | 1.04 | 1.28 | | | |
| CSIRO-Mk3.0 | 1.01 | 1.05 | 1.17 | | | |
| ECHAM5r1 | 0.98 | 1.04 | 1.25 | | | |
| ECHAM5r1-REMO_10 | 1.11 | 1.10 | 1.00 | 1.12 | 1.08 | 1.07 |
| ECHAM5r3 | 1.11 | 1.15 | 1.11 | | | |
| ECHAM5r3-RACMO | 1.18 | 1.19 | 1.21 | 1.21 | 1.22 | 1.19 |
| ECHAM5r3-REMO | 1.16 | 1.14 | 1.15 | 1.19 | 1.16 | 1.14 |
| GFDL-CM2.0 | 1.04 | 1.11 | 1.21 | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| GFDL-CM2.1 | 1.05 | 1.10 | 1.41 | | | |
| HADCM3Q0 | 1.12 | 1.17 | 1.35 | | | |
| HADCM3Q0-CLM | 1.03 | 1.10 | 1.07 | 1.02 | 1.12 | 1.04 |
| HADCM3Q3 | 1.07 | 1.12 | 1.20 | | | |
| HADCM3Q3-HADRM3 | 1.18 | 1.10 | 1.17 | 1.17 | 1.13 | 1.21 |
| IPSL-CM4 | 0.89 | 1.01 | 1.36 | | | |
| MIROC3.2 | 0.94 | 1.03 | 1.19 | | | |
| MIUB | 0.95 | 1.09 | 1.24 | | | |
| MRI-CGCM2.3.2 | 1.05 | 1.09 | 1.34 | | | |
| MEAN GCMs | 1.02 | 1.08 | 1.26 | | | |
| MEAN RCMs | 1.13 | 1.13 | 1.12 | 1.14 | 1.14 | 1.13 |

For the remaining part of this study the results for the RCMs will refer to those obtained by the delta method, except when stated differently. In Table 3.3 changes in the mean precipitation and the standard deviation of the 5-day precipitation sums are shown. The mean precipitation increases in winter and decreases in summer. For the GCM simulations the increase in the standard deviation of the 5-day precipitation sums is larger than the increase in the mean. This is consistent with the relatively large changes in the upper tail of the distribution ($P_{90}$, $\overline{E}$ ) in these simulations. For both the GCM and RCM simulations the decrease in mean summer precipitation is accompanied by an increase in the standard deviation of the 5-day precipitation sums.

**Table 3.3.** Relative changes in mean precipitation and the standard deviation (σ) of the 5-day precipitation sums after the transformation of the observations according to the changes in the GCM and RCM simulations. The changes are shown for the winter half-year (October - March) and the summer half-year (April-September).

| | Winter | | Summer | |
|---|---|---|---|---|
| | Mean | σ | Mean | σ |
| Mean GCMs | 1.08 | 1.15 | 0.88 | 1.02 |
| Mean RCMs | 1.13 | 1.12 | 0.91 | 1.06 |

### 3.4.2 Precipitation extremes in short and long time series from the GCM-RCM ensemble

To assess the possible future change in the occurrence of extreme precipitation, the maximum 10-day basin-average precipitation amounts in the winter half-year from the transformed time series for future climate conditions were compared with those in the observed time series for the original 35-year series as well as the resampled 3,000-year series (Figure 3.5). The spread between the future 10-day precipitation amounts is small at short return periods, but becomes larger at long return periods.

For return periods between 10 and 50 year, the spread for the resampled 3,000-year series is about 25% smaller than the spread for the original 35-year series. For the 3,000-year series, the total ensemble spans a range between almost no change compared to the observations to an increase of about 30% at the longest return periods.

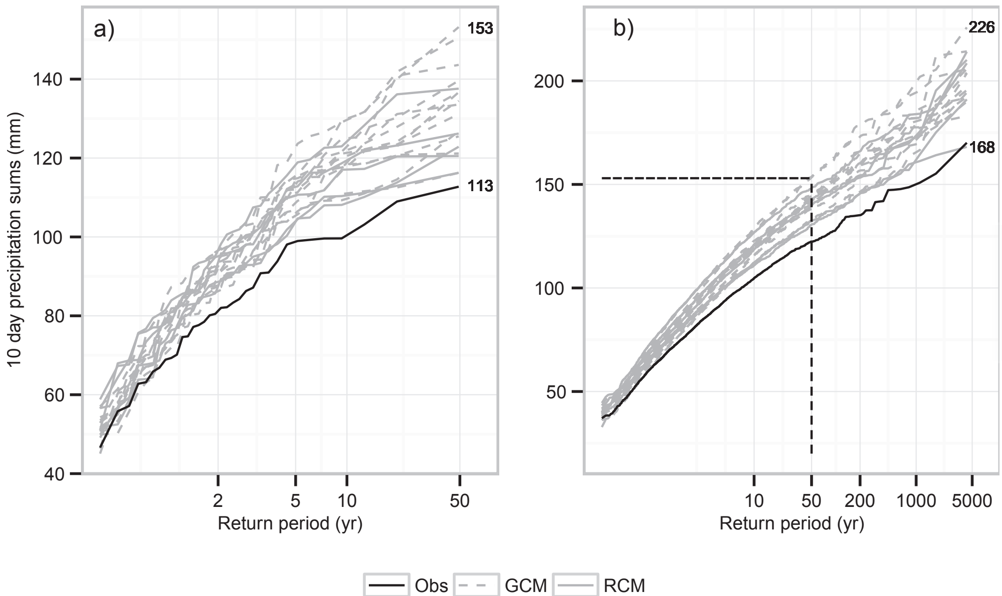


**Figure 3.5.** Gumbel plots of the maximum 10-day basin-average precipitation in winter (October-March) for the future climate (end of the 21st century) from the short time series of transformed observations - 35 year, panel (a) and those from the long time series of transformed resampled observations – 3,000 year, panel (b). The black line represents the maximum 10-day basin average precipitation sums in the (resampled) observations; the dashed grey lines refer to transformed observations based on the 13 GCM simulations and the solid grey lines refer to the 5 RCM simulations. The horizontal and vertical dashed black lines in the right panel mark the extension of the left panel.

### 3.4.3 Range of return levels of maximum 10-day precipitation sums in the GCM and RCM ensemble

In Figure 3.6 four return levels of the 10-day winter maximum basin-average precipitation for 2081-2100 are shown. These return levels are based on the 3,000-year resampled time series. The return levels were derived empirically from the ordered sample of the 10-day maxima. For the 1,000-year return level a distribution was fitted to the 15 largest values using an approach due to Weissman (1978), because of the small number of exceedances of this return level (see Supplementary information A2). The return levels from the 3,000-year resampled observations are inserted in Figure

3

3.6 as the references representing current climate conditions. For the bias corrected RCM output from the Rheinblick2050 project, each return level for the future climate was obtained by multiplying the relative difference in that return level between the future and control simulation with the reference value.

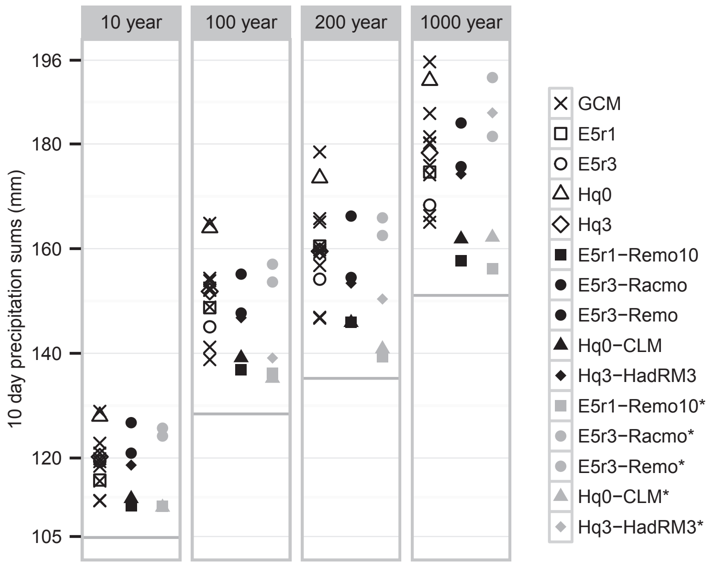


**Figure 3.6.** Ranges of return levels of 10-day basin-average precipitation for four return periods for the future climate (end of 21st century). The results are shown for the transformed observations based on the RCM and GCM ensembles and for the bias corrected RCM output from the Rheinblick2050 project. All GCM results are plotted in the first column of symbols. Open symbols represent GCM simulations that force at least one RCM; crosses refer to the results from the other GCM simulations. The second column represents transformed observations based on RCM simulations while the third column refers to the bias corrected RCM output. The RCMs are indicated by the same symbol as used for the driving GCM (in the first column). The grey horizontal lines denote the return levels of the 10-day basin-average precipitation from the reference observations (i.e. the current climate).

For the 10-year return level, the mean and spread in the GCM ensemble are comparable to those in the (delta method) RCM ensemble. For the 100-, 200- and 1,000-year return levels, the mean for the future period in the GCM ensemble is larger than the mean in the RCM ensemble. The spread within the GCM ensemble is slightly larger than the spread within the RCM ensemble for these return levels. This may be attributed to the larger size of the GCM ensemble (13 compared to five for the RCM ensemble). While the two RCM simulations that are forced by ECHAM5r3 show larger return levels of 10-day maximum basin-average precipitation than the driving GCM, all other RCM simulations show lower return levels than the forcing GCM, in agreement with the changes in $\overline{E}$ presented in Table 3.2. In particular for CLM the difference with the signal from the driving GCM is large for all return periods. For the RCM simulations, the changes in the return levels obtained from the bias corrected model output are comparable to those generated with the delta method.

## 3.5 Discussion and conclusions

This study explored the options to expand an existing range of RCM projections of changes in extreme multi-day precipitation in the Rhine basin, using an ensemble of GCM projections. The results of this study allow for a number of conclusions.

First, the selection of RCMs used in the Rheinblick2050 project does not appear to be strongly biased with respect to the multi-day extreme precipitation change imposed by the small ensemble of driving GCMs. As shown in Figure 3.6, the small number of driving GCMs for the RCM simulations from the Rheinblick2050 project covers the ranges deduced from the ensemble of 13 GCM simulations fairly well; the driving GCMs do not form a cluster or contain major outliers. When we look at the total ensemble we see that the ranges covered by the RCM simulations and the GCM simulations are similar. The ARPEGE-HIRHAM5 simulation, which was excluded in the present study, does not alter this result, because of its intermediate changes with respect to the other RCM simulations from the Rheinblick2050 project. (see 63-64 pp. of the Rheinblick2050 report; Görgen et al. 2010).

Second, for the RCM simulations the advanced non-linear delta method applied in this study generates a range of extreme multi-day precipitation changes that is similar to the range obtained directly from the bias corrected RCM simulations from the Rheinblick2050 project. This gives confidence in the application of the advanced non-linear delta method, using an ensemble of model projections. Responses derived from individual RCMs did show modest sensitivity to the selected method, but their ranking is similar for the two methods, which confirms our confidence in the advanced delta method.

Third, the multi-day extreme precipitation signal deduced from the RCMs is not trivially related to the response derived from the driving GCMs. For three out of five RCM-GCM combinations, the RCM output leads to a smaller change of extreme 10-day precipitation sums than the corresponding GCM output. The two RCMs forced by ECHAM5r3 showed an increase in the change of the extreme 10-day precipitation sums, compared to the GCM output. Especially at long return periods, the individual paired GCM and RCM simulations show systematic differences. This could indicate that the RCMs have an influence on the signal of their driving GCMs, but the small number of simulations explored here does not permit a firm conclusion on the origin, nor robustness of this difference. Further research with larger ensembles and systematic exploration of potential causes is needed. Possible causes of this response are locally generated natural variability (to be tested with larger ensembles), different physical expressions or parameterizations at higher spatial resolution, or dynamical/physical feedbacks that are represented differently by the driving GCM and the nested RCM.

The advanced delta method applied in this study is useful as it is relatively cheap and there is no bias in the reference time series. However, it has also some limitations. Since it is not physically but statistically based it potentially ignores relevant processes or feedbacks. The delta method as applied here neglects changes in the shape of the right tail of the distribution, by using a linear scaling of the excess above $P_{90}$. It is, however, not possible to obtain reliable estimate of changes in the shape of the upper tail of the distribution from relatively short climate model simulations. This leads to a large uncertainty about the change in extremes, which is not taken into account in the present study. In addition the delta method required some subjective choices regarding temporal and spatial smoothing to control noise due sampling uncertainty. In particular, the degree of temporal smoothing has some influence on the range of the relative changes of the 10-year return level of 10-day basin-average precipitation. As for other methods, the results of the delta method are influenced by sampling uncertainty resulting from the limited length of the observed and climate model time series, especially for long return periods.

For developing climate adaptation measures that deal with (future) flood risk, it is important to have knowledge about the changes in precipitation extremes. The results of this study provide an opportunity to base adaptation measures on an ensemble of 18 climate model simulations, which for current standards can be considered a large ensemble. The range of future changes in extreme multi-day precipitation, based on an ensemble of both GCMs and RCMs, gives more insight in the possible upper and lower bound of such changes, which is important information for water managers and flood risk studies (Ward, et al., 2013). Figure 3.6 shows that using a sub-sample of GCM or RCM results alone could lead to an underestimation of the uncertainty range of future return levels, in particular for long return periods. Ideally, multi-model ensembles should therefore contain both RCM and GCM based results. However, as long as the RCMs and GCMs show different responses and the nature of these differences is unexplained, the authors recommend to present the responses for the different model ensembles separately. This allows the user of this information to become aware that differences in the responses are (at least in part) related to differences in the type of climate model used.

**Acknowledgements** This research was carried out in the framework of the Dutch National Research Programme 'Climate changes Spatial Planning', as part of the project 'Attention for Safety 2' and in the framework of the Dutch National Research Programme 'Knowledge for Climate'. We thank Philip Ward, Jeroen Aerts and Otto de Keizer for their participation in the project and discussion on the methods, and Geert Jan van Oldenborgh for his comments on an earlier version of the manuscript.

Chapter 4

# Uncertainty in the future change of extreme precipitation over the Rhine basin: the role of internal climate variability

This chapter has been submitted as:
Van Pelt, S. C., Beersma, J.J., Buishand, T.A., Van den Hurk, B.J.J.M, &. Schellekens, J. Uncertainty in the future change of extreme precipitation over the Rhine basin: the role of internal climate variability. *Climate Dynamics.*

# Abstract

Future changes in extreme multi-day precipitation will influence the probability of floods in the river Rhine basin. In this study the influence of internal climate variability on the spread of the changes projected by climate models at the end of this century (2081-2100) is quantified for a 17-member ensemble of a single Global Climate Model (GCM) and results from the CMIP3 ensemble. All climate models were driven by the IPCC SRES A1B emission scenario. An analysis of variance (ANOVA) model is formulated to disentangle the contributions from systematic differences between GCMs and internal climate variability. Both the changes in the mean and characteristics of extremes are considered. To estimate variances due to internal climate variability a bootstrap method was used. The changes from the GCM simulations were linked to the local scale using an advanced non-linear delta change approach. This approach uses climate responses of the GCM to transform the daily precipitation of 134 sub-basins of the river Rhine. The transformed precipitation series was used as input for the hydrological HBV model to simulate future river discharges. Internal climate variability accounts for about 30% of the total variance in the projected climate trends of average winter precipitation and explains a larger fraction of the total variance in the projected climate trends of extreme precipitation in the winter half-year. There is a good correspondence between the direction and spread of the changes in the return levels of extreme river discharges and extreme 10-day precipitation over the Rhine basin. This suggests that also for extreme discharges a large fraction of the total variance can be attributed to internal climate variability.

## 4.1 Introduction

Decision makers in a wide variety of sectors are increasingly asking for quantitative projections of changes in climate on regional scales. Such projections are available from the outputs of (downscaled) Global Climate Models (GCMs), or directly from Regional Climate Models (RCMs). The outputs from the climate models can be further processed by impact models, e.g. hydrological models. The climate change projections are subject to large uncertainties, for example, even the sign of the change in mean precipitation varies across models in many areas (Meehl et al. 2007). An important issue for decision makers and scientists is how to rank and quantify these uncertainties. The relative contribution of emission induced climate change to the simulated changes is important for decision makers developing adaptation strategies.

The uncertainties of climate projections originate from three sources, namely model uncertainty, scenario uncertainty and uncertainty due to internal climate variability (Hawkins and Sutton 2009). Model uncertainties arise from the way specific processes and feedbacks are modelled. Scenario uncertainty originates from incomplete knowledge of external factors influencing the climate system, for example future emission of greenhouse gases or population growth. Internal climate variability is the natural variability of the climate system and uncertainty arises from non-linear dynamical processes and unknown initial conditions. The relative importance of these three sources of uncertainty varies with prediction lead time and with the scale of spatial and temporal averaging (Hawkins and Sutton 2009; Räisänen 2001). For multi-decadal time scales and global spatial scales, the dominant uncertainties for temperature are model uncertainty and scenario uncertainty. The importance of internal climate variability increases at shorter time scales (Cox and Stephenson 2007) and smaller spatial scales (Hawkins and Sutton 2009).

A number of studies have demonstrated that internal climate variability is a much more important factor for projected changes in precipitation than for temperature (Murphy et al. 2004; Räisänen 2001). Giorgi and Bi (2009) studied the time at which the magnitude of the multi-model ensemble mean precipitation change exceeds the total interexperiment standard deviation of the changes in the mean precipitation. They found that for most regions this occurs somewhere in the 21$^{st}$ century and for some regions even in the early 21$^{st}$ century. These authors further stressed that the contribution of inter-model spread to the total interexperiment standard deviation is substantially larger than that of internal multi-decadal climate variability. Hawkins and Sutton (2011) continued on this study and found that internal climate variability is the most important source of uncertainty for many regions for lead times up to 30 years. Model uncertainty is generally dominant thereafter and scenario uncertainty is very small. These results apply to large regions ($\approx 2500 \times 2500$ km$^2$). Rowell (2012) studied the sources of uncertainty in the changes in mean precipitation at the end of the 21$^{st}$ century in four GCM ensembles. He found that model uncertainty is the dominant source of uncertainty for the projected changes in tropical and polar regions, and that internal climate variability becomes more important at mid-latitudes.

The papers cited above deal with the contribution of internal climate variability to the total uncertainty of the change in mean precipitation. For many regions, also the changes in extreme precipitation are important as they can have large impacts on flood risk. The uncertainty of the changes in extreme precipitation, has only been studied to a limited extent. Räisänen and Joelsson (2001) compared the changes in the annual mean and maximum precipitation in two 10-year control and 10-year future regional climate model simulations driven by different GCMs. They concluded that the differences between the changes in these two model experiments could be largely explained by internal climate variability as a result of the short lengths of the climate model simulations. Brekke and Barsugli (2013) studied the sources of uncertainty in the changes in the 2-year and 100-year return levels of the local 1-day annual maximum precipitation in the United States (US). Both model uncertainty and internal climate variability were found to be important sources of the uncertainty in the projected changes in these return levels for the end of the 21$^{st}$ century over much of the US.

This paper focuses on the contribution of internal climate variability to changes in extreme precipitation and discharge in the river Rhine basin. For current and future water management in the densely populated Rhine basin, flood risk is one of the major concerns. Van Pelt et al. (2012) gave various estimates of the future changes in extreme precipitation over the basin using different climate model simulations. The question how far the spread of these estimates could be ascribed to internal climate variability was not addressed in that work. To assess the contribution of internal climate variability two ensembles of GCM simulations are considered in this study: one ensemble with different GCMs and one ensemble using multiple realisations (with perturbed initial conditions) of a single GCM.

A bootstrap method was applied to estimate the variance of the changes in three precipitation characteristics due to internal climate variability. This variance is compared to the total interexperiment variance of the changes in the ensemble. The non-linear delta method of Van Pelt et al. (2012), in combination with time series resampling, was used to obtain representative series of daily precipitation for future climate conditions at the scale of the Rhine basin consistent with the changes in the various GCM simulations. Return levels of extreme 10-day precipitation, associated with return periods between 10 and 1000 years were then derived for the end of the 21$^{st}$ century. The spread of these return levels in the two GCM ensembles is compared. A similar comparison is made for extreme river discharges in the Rhine basin. River discharge was obtained by driving a hydrological model with the transformed precipitation and temperature time series.

The paper is structured as follows: The two GCM ensembles and the observed data are described in Section 4.2. Methodological issues, including an analysis of variance to distinguish internal climate variability from the variability due to systematic differences between GCMs, are dealt with in Section 4.3. The results of the analysis of variance are discussed in Section 4.4. The return levels of extreme 10-day precipitation and river discharge are presented in Section 4.5. In Section 4.6 the findings and conclusions are discussed.

## 4.2 Climate model ensembles and observations

In Table 4.1 an overview is given of the two GCM ensembles that have been used for this study. Both ensembles refer to transient GCM simulations, using the IPCC SRES A1B scenario for future greenhouse gas emissions. The GCM simulations from the Coupled Model Intercomparison Project Phase 3 (CMIP3) archive were conducted with different GCMs. The ESSENCE ensemble (Sterl et al. 2008) is a 17-member ensemble simulation with the ECHAM5/MPI-OM coupled climate model which has been developed at the Max-Planck-Institute for Meteorology in Hamburg. All members share the A1B greenhouse gas forcing, but their initial state of the atmosphere was perturbed. This results in different realizations due to internal climate variability in the modelling system. The grid size and structure vary between the GCMs, therefore the output was regridded to a common 2° lat by 2.5° lon grid. At this resolution the Rhine basin is covered by eight grid cells (see Fig. 4.1). For all GCMs a 35-year control period (1961-1995 from the historically forced part of the simulation until 2000) and a 20-year future period (2081-2100 from the SRES A1B forced part of the simulation after 2000) were used, see also Van Pelt et al. (2012). The 20-year future period was chosen because this was the longest common future period for which daily precipitation was available for all GCMs.

4

**Table 4.1.** GCM simulations used in this study.

| Ensemble | GCM | GCM references |
|---|---|---|
| CMIP3 | CGCM3.1T63 | Flato (2005) |
| | CNRM-CM3 | Salas-Mélia et al. (2005) |
| | CSIRO-Mk3.0 | Gordon et al. (2002) |
| | ECHAM5r1 | Roeckner et al. (2003) |
| | GFDL-CM2.0 | Delworth et al. (2006) |
| | GFDL-CM2.1 | |
| | HADCM3Q0 | Gordon et al. (2000) |
| | HADCM3Q3 | |
| | IPSL-CM4 | Marti et al. (2006) |
| | MIROC3.2 hires | Hasumi and Emori (2004) |
| | MIUB | Min et al. (2005) |

| | | |
|---|---|---|
| | MRI-CGCM2.3.2 | Yukimoto et al. (2006) |
| ESSENCE | ECHAM5 | Sterl et al. (2008) |

For the reference years 1961-1995, observations of precipitation and temperature for the Rhine basin were available from the International Commission for the Hydrology of the Rhine basin (CHR). This CHR-OBS dataset (De Wit and Buishand 2007) contains area-averaged daily precipitation and temperature for 134 sub-basins, aligned with the spatial structure of the hydrological HBV (Hydrologiska ByrånsVattenbalansavdelning) model (Bergström and Forsman 1973) of the Rhine basin, see also Figure 4.1. A newer and longer precipitation data set has become available (Photiadou et al. 2011), but this was not used in the present study because the HBV model was calibrated to the old CHR-OBS dataset. The HBV model is a semi-distributed conceptual model for the entire Rhine basin upstream from Lobith, where the river enters the Netherlands. Daily precipitation and temperature time series are used as input for the HBV model. The model uses temperature to calculate potential evapotranspiration and snow accumulation and -melt.

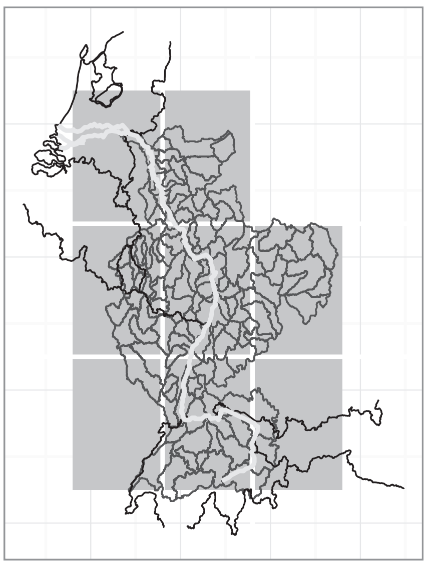

**Figure 4.1.** The Rhine basin covered by 2°lat by 2.5°lon GCM grid cells. The grey lines represent the 134 HBV sub-basins.

## 4.3 Methodology

### 4.3.1 Delta change approach and resampling

An advanced delta change approach was used to transform the daily precipitation and temperature observations in each HBV sub-basin into time series that are representative of future conditions at this scale consistent with the GCM climate change signal. Advanced, means here that the method accounts for the fact that changes in extreme precipitation may be different from changes in the mean. The approach is extensively described in Van Pelt et al. (2012). The transformed precipitation and temperature series were used as input for the HBV model to determine future discharge changes of the Rhine (see Section 4.5). For precipitation the procedure is presented schematically in Figure 4.2. First, a non-linear transformation is applied to the aggregated observed 5-day precipitation amounts of the eight GCM grid cells. A 5-day aggregation level was considered in this transformation because flooding in the Rhine basin often occurs after multi-day precipitation (Disse and Engel 2001; Ulbrich and Fink 1995). In a subsequent step the (observed) daily precipitation amounts of the sub-basins are adjusted to the transformed 5-day precipitation amounts at the GCM grid cells.

4

The transformation of the 5-day precipitation amounts can be mathematically represented as (see also Leander and Buishand 2007):

$$P^* = aP^b \qquad \text{for} \qquad P \leq P_{90}^{\mathrm{O}} \tag{4.1}$$

$$P^* = \bar{E}_{90}^{\mathrm{F}}/\bar{E}_{90}^{\mathrm{C}} \cdot \left(P - P_{90}^{\mathrm{O}}\right) + a\left(P_{90}^{\mathrm{O}}\right)^b \qquad \text{for} \qquad P > P_{90}^{\mathrm{O}} \tag{4.2}$$

where $P$ and $P^*$ respectively, represent subsequent observed and transformed (i.e. the future) 5-day precipitation sums at a GCM grid cell, $P_{90}^{\mathrm{O}}$ denotes the 90% quantile of the observed 5-day precipitation amounts, and $a$ and $b$ are the transformation coefficients ($a$, $b$ > 0). These coefficients were derived from the changes in the 60% and 90% quantiles of the (non-overlapping) 5-day precipitation sums in the GCM simulation, between the periods 1961-1995 and 2081-2100. The 60% quantile was chosen because this quantile is generally closer to the mean than the median due to the positive skewness of the precipitation distribution. The 90% quantile is in the left tail of the distribution of the seasonal maximum 5-day precipitation amounts. For instance, in a 3-month season, this quantile is exceeded with probability 0.85 assuming independence between the 5-day precipitation amounts. For 5-day precipitation amounts exceeding $P_{90}^{\mathrm{O}}$ a separate equation (4.2) was used to better reproduce the changes in the upper tail of the precipitation distribution. It scales the excess $E_{90}=P-P_{90}^{\mathrm{O}}$ with the change in the mean excess ($\bar{E}_{90}^{\mathrm{F}}/\bar{E}_{90}^{\mathrm{C}}$) in the GCM simulation. This scaling changes the slope of an extreme-value plot of 5-day precipitation maxima but not its curvature, see Van Pelt et al. (2012) for details. The mean excesses for the control and future periods were obtained as:

$$\bar{E}_{90}^{\mathrm{C}} = \sum E_{90}^{C}/n^{C} \qquad \text{and} \qquad \bar{E}_{90}^{\mathrm{F}} = \sum E_{90}^{F}/n^{F} \tag{4.3}$$

where $n^{\mathrm{C}}$ and $n^{\mathrm{F}}$ are the number of 5-day periods in which the 90% quantile is exceeded in the control and future period, respectively.

The 60% and 90% quantiles and the mean excesses were determined for each calendar month separately. To reduce sampling variability (due to the finite length of the available time series) of the parameters in Eqs. 4.1 and 4.2, these quantities were temporally smoothed using a 3-month moving average with a weight of ½ placed on the calendar month of interest and weights of ¼ on the preceding and following calendar months. Sampling variability was reduced further by assuming that *b* and the scaling factor of the excesses are constant over the eight GCM grid cells covering the Rhine basin. The medians of the temporally smoothed estimates of these parameters over the eight grid cells for each calendar month were used in Eqs. 4.1 and 4.2.

After the transformation of the 5-day precipitation at the GCM grid cells, the daily precipitation amounts for the sub-basins are scaled with a change factor $R = P^*/P$ (see Fig. 4.2, lower panels). This change factor is calculated for each subsequent 5-day period and each grid cell.

Temperature time series representative of the future climate were also obtained by using a delta change method. The observed daily temperature was transformed for each sub-basin taking into account the changes in the mean and standard deviation of the daily temperatures from the GCM simulation (Shabalova et al. 2003):

$$T^* = \frac{\sigma^{\mathrm{F}}}{\sigma^{\mathrm{C}}}(T - \bar{T}^{\mathrm{O}}) + \bar{T}^{\mathrm{O}} + \bar{T}^{\mathrm{F}} - \bar{T}^{\mathrm{C}} \tag{4.4}$$

where $T$ and $T^*$ respectively, represent the observed and transformed daily temperature. $\bar{T}^{\mathrm{O}}$ is the mean of the observed daily temperature. $\bar{T}^{\mathrm{F}}$, $\sigma^{\mathrm{F}}$ are the mean and standard deviation of the daily temperature in the future climate and $\bar{T}^{\mathrm{C}}$, $\sigma^{\mathrm{C}}$ are the mean and standard deviation of the daily temperature in the control climate. As for precipitation the mean and standard deviation were determined for each calendar month and each grid cell, but in this case no spatial smoothing was applied. The standard deviation was temporally smoothed using the same 3-month moving average as for the quantiles and mean excesses of the 5-day precipitation sums.

To estimate return levels of 10-day precipitation and discharge associated with long return periods (up to 1,000 years, which means that the level is exceeded each year with a probability of 1/1,000) 3,000-year synthetic sequences of daily precipitation and temperature were generated by nearest-neighbour resampling from the 35-year record of historical observations. These long synthetic sequences were subsequently transformed to future time series using the delta change methods for precipitation and temperature as described above and used as input for the hydrological model.

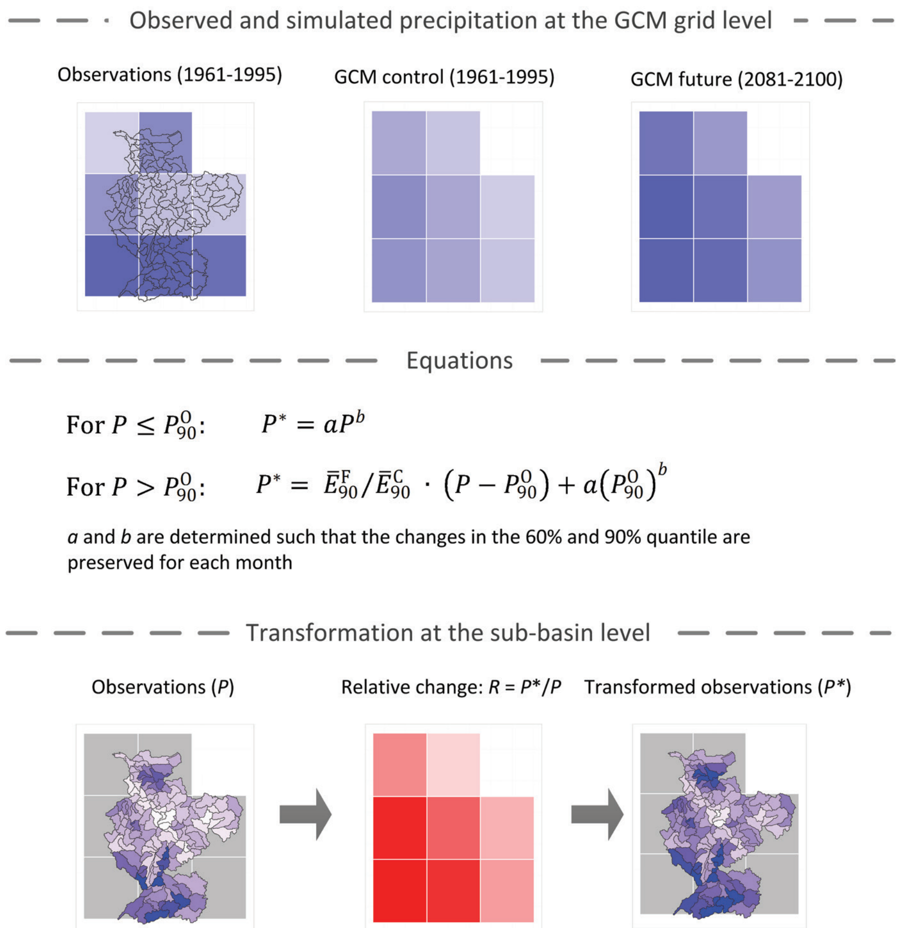


**Figure 4.2.** Schematic overview of the advanced delta change approach. The upper panels represent the observed 5-day precipitation at the GCM grid level and the simulated 5-day precipitation for the control and future climates. The observed precipitation at the sub-basin level was aggregated to the GCM grid cells by taking a weighted average over the sub-basins. The middle panel shows the equations for the transformation of the 5-day precipitation sums at the GCM grid cell scale (with transformation coefficients $a$, $b$ and $\bar{E}_{90}^{F}/\bar{E}_{90}^{C}$). The lower panels demonstrate the transformation of the daily precipitation of the sub-basins using a change factor $R$, which is the ratio of the transformed ($P^{*}$) and the observed ($P$) 5-day precipitation amount at the GCM grid cells (for each sub-basin within a grid cell and for each day within a 5-day period the sub-basin precipitation is multiplied with the same $R$-value). This figure is based on Figure 1 in Van Pelt et al. (2012).

Details of the resampling procedure of the time series are given in Van Pelt et al. (2012).

### 4.3.2 Analysis of variance

An analysis of variance (ANOVA) model was formulated to disentangle the contributions from model uncertainty, i.e. systematic differences between GCMs, and internal climate variability. For each GCM experiment the simulated change $x_i$ can be represented as (Räisänen 2001):

$$x_i = M + \delta_i + \eta_i \tag{4.5}$$

where $M$ is the mean change between the current and future climate in an infinite number of GCM simulations under the same forcing scenario, $\delta_i$ is a model-related random deviation and $\eta_i$ is a random deviation associated with internal climate variability in experiment $i$. In this study $x_i$ refers to the relative change in the mean, the 90% quantile ($P_{90}$) or the mean excess ($\overline{E}_{90}$) of the 90% quantile. It is assumed that the deviations $\delta_i$ and $\eta_i$ have both zero means and that they are uncorrelated, both within each experiment, i.e. $E(\delta_i\eta_i)=0$, and between experiments.

For an ensemble of $k$ GCM experiments, the total interexperiment variance $V$ is defined as:

$$V = \frac{1}{k-1}\sum_{i=1}^{k}(x_i - \bar{x})^2 \tag{4.6}$$

where $\bar{x}$ is the average of the $x_i$'s. For the ANOVA model in Eq. (4.5), it can be shown that the mean of $V$ is given by:

$$E(V) = D + \frac{1}{k}\sum_{i=1}^{k} N_i \tag{4.7}$$

where $D = var\ (\delta_i) = E\ (\delta_i^2)$ and $N_i = var\ (\eta_i) = \mathrm{E}\ (\eta_i^2)$. This corresponds to Eq. (8) in Räisänen (2001) with his variable $e^2$ equal to $(k\text{-}1)V/k$. Thus, the variance due to internal climate variability $N_i$ varies from model to model, while the systematic differences between the GCMs are expressed by the variance $D$.

The variance component due to model uncertainty ($D$) can be estimated from the total interexperiment variance ($V$), if we know the variances due to internal climate variability ($N_i$) for each GCM experiment. To determine $N_i$, each GCM should be run multiple times with different initial conditions. This would result in an ensemble similar to ESSENCE for each GCM. However, such ensembles were not available for the GCMs used in this study. Therefore, we used a bootstrap method to estimate the variances due to internal climate variability $N_i$. This leads to the following estimate of the second term of the right hand side of Eq. (4.7):

$$\widehat{N} = \frac{1}{k}\sum_{i=1}^{k}\widehat{N}_i \tag{4.8}$$

where $\widehat{N_i}$ is the bootstrap estimate of $N_i$.

The bootstrap samples were generated by taking random samples with replacement from the 35-year time series for the control period and the 20-year time series for the future period. The new 35-year and 20-year bootstrap time series for each GCM simulation were created separately by selecting individual years from either the control or the future period. This process was repeated $B$=1000 times, so we get $B$ estimates for the changes in the mean, $P_{90}$ and $\overline{E}_{90}$. $\widehat{N_i}$ was taken as the sample variance of these estimates. A balanced bootstrap was chosen, which means that taken over all bootstrap samples the individual years are equally represented. The bootstrap assumes independence between years and absence of systematic trends within the control and future GCM periods. Räisänen (2001) demonstrates that for precipitation the estimate of internal climate variability is not much affected by these assumptions. The bootstrap was also applied to the members of the ESSENCE ensemble. For the latter, the estimated variances from the bootstrap should correspond to the total interexperiment variance because the model related deviation $\delta_i$ equals zero in this ensemble by definition.

## 4.4 Results



### 4.1.1 Influence of internal climate variability on changes in the mean

In Figure 4.3 the changes in the basin-average precipitation and temperature in the CMIP3 ensemble projected for the end of the 21$^{st}$ century are compared with those in the ESSENCE ensemble. The figure shows that for the summer half-year (April-September) the spread of the relative changes in precipitation in the CMIP3 ensemble is much larger than the spread in the ESSENCE ensemble. Assuming a similar internal climate variability within the ESSENCE and the CMIP3 ensembles, the model uncertainty would be considerably larger than the uncertainty due to the internal climate variability. For the winter half-year (October-March), the spread between the changes in the CMIP3 simulations is more similar to that in the ESSENCE ensemble, which suggests that in winter the influence of internal climate variability on the relative change in precipitation is large. For temperature, the spread between the different CMIP3 GCM simulations is much larger than the spread within the ESSENCE ensemble both for the summer and winter halves of the year and the whole year. This confirms the results of other studies that for temperature the contribution of internal climate variability to the total interexperiment variance ($V$) is smaller than for precipitation (Murphy et al. 2004; Räisänen and Palmer 2001). The remaining part of this study only focuses on changes in winter half-year precipitation, as these changes are most important for flood risk in the river Rhine basin.

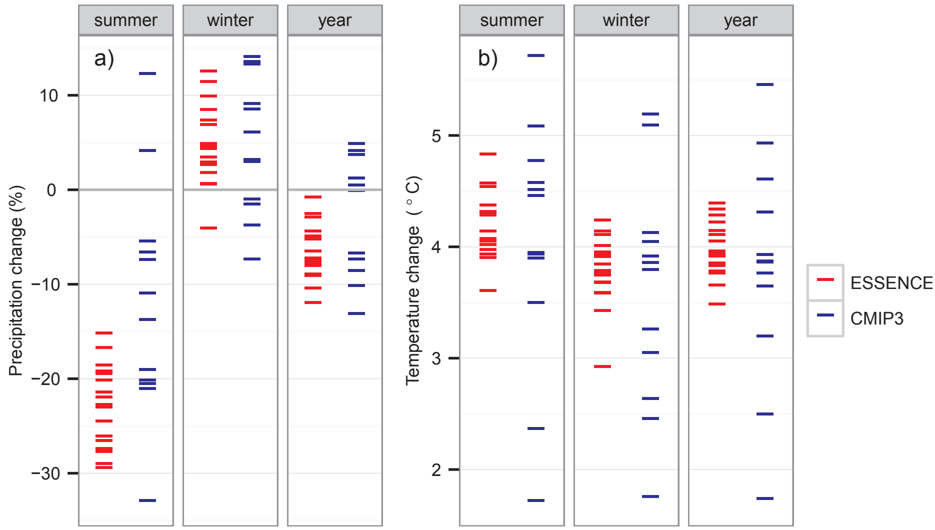


**Figure 4.3.** Relative change in average precipitation (a) and absolute change in average temperature (b) in the Rhine basin for the summer and winter halves of the year and the whole year. The changes refer to changes between the control (1961-1995) and future (2081-2100) climates.

A good indicator for the spread of the relative changes between GCMs due to internal climate variability is the coefficient of variation (*CV*) of the precipitation sums in the winter half-year, i.e the ratio of their interannual standard deviation ($\sigma$) to their mean. Assuming independence between years, the variance of the relative change $x$ can be approximated as (Stuart and Ord 1987):

$$\operatorname{var} x \;\approx\; \mu_x^2 \left[\frac{(CV^C)^2}{n^C} + \frac{(CV^F)^2}{n^F}\right] \tag{4.9}$$

where $\mu_x$ is the expected relative change, $CV^C$ and $CV^F$ are the *CV*s for the control ($^C$) and future ($^F$) periods, and $n^C$ and $n^F$ are the number of years in the control ($^C$) and future ($^F$) periods.

Table 4.2 shows that the *CV* for the CMIP3 ensemble is smaller than for the ESSENCE ensemble, both for the control and the future period. According to Eq. 4.9, the spread of the relative changes in the average winter precipitation should then be smaller for the CMIP3 ensemble than for the ESSENCE ensemble if these changes were purely due to internal climate variability. This is not the case in Figure 4.3 owing to systematic differences between the GCMs in the CMIP3 ensemble. The difference in the spread of the relative changes in the CMIP3 and ESSENCE ensembles in Figure 4.3 underestimates the contribution of the systematic differences between the GCMs because of the smaller internal climate variability in the CMIP3 ensemble.

**Table 4.2.** Coefficient of variation ($CV$) and standard deviation ($\sigma$) of the winter half-year precipitation sums for the control ($^C$) and future ($^F$) periods. The total interexperiment variance $V$ and the estimate $\hat{N}$ of the variance due to internal climate variability are also given (with standard errors in parentheses for the ESSENCE ensemble).

| | $CV^C$ | $CV^F$ | $\sigma^C$ | $\sigma^F$ | $\hat{N}$ | $V$ |
|---|---|---|---|---|---|---|
| | | | mm | mm | *10$^{-3}$ | *10$^{-3}$ |
| CMIP3 | 0.12 | 0.14 | 62.0 | 75.3 | 1.61 | 5.18 |
| ESSENCE | 0.15 | 0.17 | 91.6 | 107.8 | 2.21 (0.12) | 1.82 (0.51) |
| Observations | 0.22 | - | 102.4 | - | - | - |

Table 4.2 also shows that the control periods of the CMIP3 and the ESSENCE ensembles underestimate both the $CV$ and the interannual standard deviation of the observed precipitation. This underestimation of the internal climate variability in the ESSENCE and CMIP3 ensembles implies that the spread of the relative changes in the basin-average winter precipitation in both ensembles (as shown in Figure 4.3) is probably too small.

Table 4.2 further compares the total interexperiment variance ($V$) with the estimate of variance due to internal climate variability ($\hat{N}$), the latter of which was obtained using a bootstrap method (Section 4.3.2). For the CMIP3 ensemble, $\hat{N}$ is about 30% of the total variance. For the 17 members of the ESSENCE ensemble the total variance and the estimate of the variance due to the internal climate variability are roughly equal, as expected. The small difference between $\hat{N}$ and $V$ for the ESSENCE ensemble can be related to sampling uncertainty as expressed by their standard errors. For $V$ the relative standard error is about 30% and the standard error is larger than the difference between $\hat{N}$ and $V$. The standard error of $V$ is based on 1,000 bootstrap samples of the relative changes of the ESSENCE members. The standard error ($se$) of $\hat{N}$ was obtained from:

$$se^2 = \frac{1}{k(k-1)} \sum_{i=1}^{k} \left(\hat{N}_i - \hat{N}\right)^2 \tag{4.10}$$

where $i$ refers to the individual ESSENCE members.

### 4.4.2. Influence of internal climate variability on changes in extreme multi-day precipitation

Figure 4.4 shows that the spread of the relative changes in $P_{90}$ is larger for the CMIP3 ensemble than for the ESSENCE ensemble, which suggests some influence of systematic differences between the GCMs in the CMIP3 ensemble, i.e. model uncertainty. The CMIP3 and ESSENCE ensembles show similar spread of the relative changes in $\overline{E}_{90}$, but these changes are larger for the CMIP3 ensemble. Both ensembles show an increase in $P_{90}$ and $\overline{E}_{90}$ for the end of this century. For the ESSENCE ensemble the mean change in

$\overline{E}_{90}$ is comparable with that in $P_{90}$ (and that in the average winter precipitation). The relative changes in $\overline{E}_{90}$ in the CMIP3 ensemble are larger than those in $P_{90}$ and in the average winter precipitation.

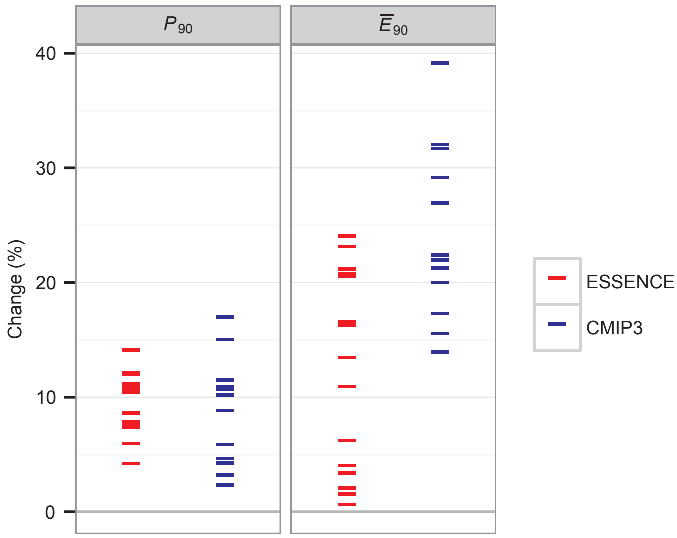


**Figure 4.4.** The relative changes in $P_{90}$ and mean excess $\overline{E}_{90}$ for the winter half-year. The results refer to the changes between the control (1961-1995) and future (2081-2100) climates.

Table 4.3 shows that for the change in $P_{90}$ the internal climate variability ( $\widehat{N}$ ) explains about 40% of the interexperiment variance $V$ of the CMIP3 ensemble. This is more than what was found for the average winter precipitation (about 30%) in Section 4.1. The spread of the relative changes of $\overline{E}_{90}$ can be fully explained by the internal climate variability. For the ESSENCE ensemble the interexperiment variance ($V$) for $\overline{E}_{90}$ corresponds roughly with the variance due to internal climate variability ( $\widehat{N}$ ), as was the case for the average winter precipitation, but for $P_{90}$, $\widehat{N}$ is twice as large as $V$. This is mainly due to the large uncertainty of $V$, as represented by its standard error. An approximate F-test shows that the differences between $\widehat{N}$ and $V$ are not significant at the 5% level. Because of the large standard error of $V$, the discrimination between model uncertainty and internal climate variability is very inaccurate for an ensemble of 15 climate model simulations. For changes in seasonal mean precipitation, Rowell (2012) found substantial sampling variability in the ratio of the model uncertainty to the total uncertainty by computing this ratio for 1,000 random samples of 17 climate models from a 280-member ensemble.

**Table 4.3.** Variance components for the relative change in the average precipitation in the winter half-year (see also Table 4.2), the 90% quantile of 5-day precipitation sums ($P_{90}$) and the mean excess ($\overline{E}_{90}$) for the CMIP3 and ESSENCE ensembles. $V$ denotes the total interexperiment variance as defined in Eq. (4.5). $\widehat{N}$ denotes the variance from internal climate variability (with the standard errors in parentheses for the ESSENCE ensemble).

| | | $\widehat{N}$ $*10^{-3}$ | $V$ $*10^{-3}$ |
|---|---|---|---|
| CMIP3 | Average | 1.61 | 5.18 |
| | $P_{90}$ | 1.17 | 2.80 |
| | $\overline{E}_{90}$ | 10.2 | 5.43 |
| ESSENCE | Average | 2.21 (0.12) | 1.82 (0.51) |
| | $P_{90}$ | 1.25 (0.06) | 0.65 (0.19) |
| | $\overline{E}_{90}$ | 7.86 (0.49) | 6.67 (1.27) |

In both ensembles the smallest values of $\widehat{N}$ are found for the 90% quantile ($P_{90}$). The variance of the relative change in a statistic is related to the $CV$s of the statistic in the control and future climate (for the variances of the relative changes in $P_{90}$ and $\overline{E}_{90}$ a similar expression as Eq. (4.9) applies). These $CV$s are shown in Table 4.4. The $CV$ of $P_{90}$ is generally smaller than the $CV$ of the average winter precipitation. The relatively low $CV$ of $P_{90}$ is due to the relatively large mean value of this statistic. The excesses ($E_{90}$ = $P$-$P_{90}{}^{0}$) have a relatively small mean value compared to $P_{90}$ and Table 4.4 shows that the mean excesses have a much larger $CV$ than $P_{90}$ and the average winter precipitation. This leads to the relatively large values of for the mean excesses in Table 4.3 and the relatively large spread for the change of the mean excess in Figure 4.4. Note further that for $P_{90}$ the $CV$s for the CMIP3 ensemble are comparable to those for the ESSENCE ensemble, in contrast to the $CV$s for the average winter precipitation.

**Table 4.4.** Coefficient of variation ($CV$) of the average precipitation in the winter half-year, the 90% quantile of 5-day precipitation sums ($P_{90}$) and the mean excess ($\overline{E}_{90}$).

| | | Average $*10^{-2}$ | $P_{90}$ $*10^{-2}$ | $\overline{E}_{90}$ $*10^{-2}$ |
|---|---|---|---|---|
| CMIP3 | Control | 2.12 | 1.76 | 5.02 |
| | Future | 3.17 | 2.88 | 6.47 |
| ESSENCE | Control | 2.46 | 1.88 | 4.86 |
| | Future | 3.68 | 2.85 | 5.93 |

## 4.5 Future changes in precipitation and discharge for long return periods

The advanced delta change method was applied to resampled 3,000-year synthetic time series of daily precipitation (see also section 4.3.1). This allowed for an analysis of return levels of extreme precipitation with associated return periods up to 1,000 years for both the CMIP3 and ESSENCE ensemble. In addition, the (transformed) resampled precipitation and temperature time series were used as input for the hydrological HBV model. With the HBV model discharge time series (of 3,000 years) were created for the river Rhine. The 1,250-year return level of the Rhine discharge at Lobith is the safety standard for dikes along the non-tidal part of the river in the Netherlands.

Both for the resampled 3,000-year sequence for the control climate and the transformed time series for the future climate, the 10-day maximum precipitation amounts in the winter half-year were determined. Return levels of these maxima are shown in Figure 4.5a for return periods from 10 to 1,000 years. For return periods less than 1,000 years the return levels were derived empirically from the ordered sample of the 10-day maxima. For the 1,000-yr return level, a distribution was fitted to the 15 largest values using an approach due to Weismann (1978). For all GCM simulations in the ESSENCE and CMIP3 ensembles, the transformation leads to an increase in the return levels. This is in line with the increase in the extreme-value characteristics $P_{90}$ and $\overline{E}_{90}$ of the 5-day precipitation sums, shown in Figure 4.4.

Although for each return period the increase in the return level is on average somewhat higher for CMIP3 than for ESSENCE, the spread within these ensembles is roughly similar. This resembles the spread of the changes in $\overline{E}_{90}$ which could have been expected because the changes in the extreme 10-day precipitation amounts are strongly related to the changes in the upper tail of the distribution of the 5-day precipitation amounts. It may therefore be assumed that the observed spread of the return levels can largely be explained by internal climate variability. Unfortunately, it is not possible to analyse the results of Figure 4.5a in a similar way as was done for the mean, $P_{90}$ and $\overline{E}_{90}$. Bootstrapping of the 3,000-year daily time series would give the variance resulting from the finite length of the resampled time series rather than the finite lengths of the GCM simulations.

In Figure 4.5b the annual maximum discharge is shown for the same return periods. The spread between the return levels is also similar for the ESSENCE and CMIP3 ensembles. The results for discharge are comparable to those for precipitation in Figure 4.5a, which suggests that the change in the 10-day maximum precipitation in the winter half-year is a good indicator for the changes in high discharge levels at Lobith. Consequently, we may assume that also for extreme discharges a large fraction of the total interexperiment variance can be attributed to internal climate variability.

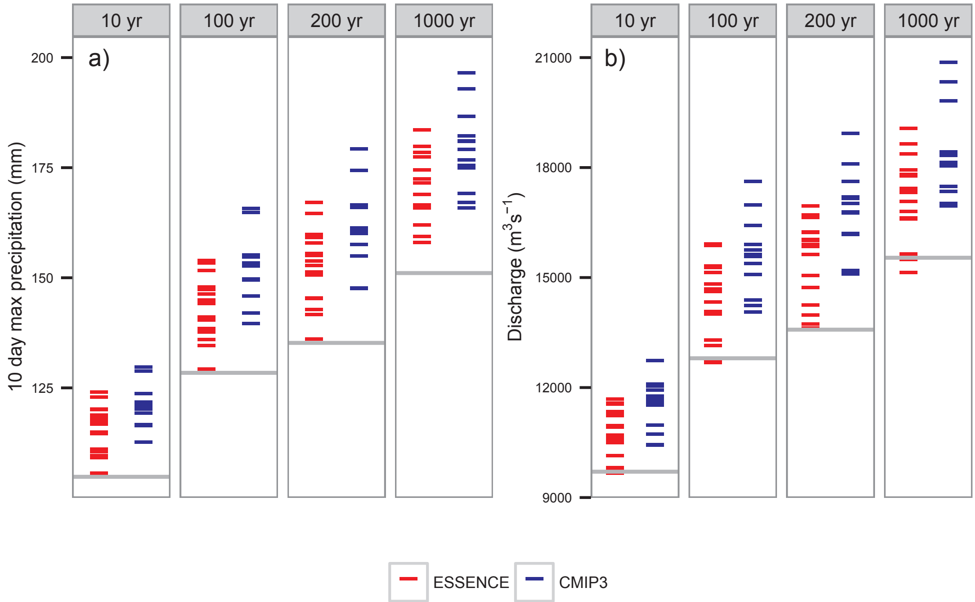


**Figure 4.5.** (a) Ranges of the return levels of the future 10-day maximum basin-average precipitation in the winter half-year for four return periods. The results are shown for the transformed resampled observations based on the CMIP3 and ESSENCE ensembles. The grey horizontal line denotes the return levels of the 10-day basin-average precipitation from the resampled observations (i.e. the reference or control climate). (b) Ranges of the return levels of future annual maximum discharge at Lobith, for the same return periods, based on the transformed resampled observations as input to the hydrological HBV model for the river Rhine.

## 4.6 Discussion and conclusions

In this paper we used the CMIP3 and ESSENCE ensembles to estimate the contribution of internal climate variability to the projected changes of mean and extreme precipitation for the end of the 21$^{st}$ century over the river Rhine basin. An ANOVA model was formulated to distinguish between the contributions from model uncertainty and internal climate variability. The results were discussed for average winter half-year precipitation and two extreme-value characteristics, $P_{90}$ and $\bar{E}_{90}$. These characteristics were important parameters in an advanced delta change method that was applied to obtain representative time series of future climate conditions at the local scale. A 3,000-year resampled time series was used to estimate return levels of extreme 10-day precipitation in the winter half-year for return periods up to 1,000 years. This long time series was used as input for the hydrological HBV model, to allow for the estimation of the return levels of extreme river discharges.

Most GCM simulations showed an increase in the average winter precipitation over the Rhine basin for the end of the 21st century. It was found that the GCMs from both the ESSENCE and the CMIP3 ensembles underestimated the variability of the observed winter-half year precipitation. All GCMs in the CMIP3 and ESSENCE ensembles showed an increase in the extreme-value characteristics $P_{90}$ and $\overline{E}_{90}$. This resulted in an increase in the return levels of the 10-day precipitation amounts for return periods from 10 to 1,000 years. The river discharge showed a similar change for these same return periods.

For the Rhine basin it is shown that about 30% of the variance of the relative changes in the basin-average winter precipitation as projected by the CMIP3 ensemble can be explained by internal climate variability. This result is comparable to what was found in other studies (Hawkins and Sutton 2011; Räisänen 2001). Our study is the first to focus on the contribution of internal climate variability to changes in winter precipitation maxima over the Rhine basin. The results are, however, not always directly comparable with those in other studies because of differences in temporal averaging (annual versus seasonal means) and spatial scales, and because of different GCM ensembles. Our results suggest that the contribution of internal climate variability increases towards more extreme precipitation. The variance of the relative changes in the mean excess $\overline{E}_{90}$ in the CMIP3 ensemble could be totally explained by internal climate variability. This suggests that the spread in the estimated return levels of extreme 10-day precipitation and river discharges for the end of the 21st century is mainly due to internal climate variability rather than systematic differences between climate models. This is in any case at variance with the results of Brekke and Barsugli (2013) for the changes in the return levels of 1-day annual maximum precipitation in the US at the end of the 21st century for 9 members of the CMIP3 ensemble where model uncertainty was a significant source of uncertainty. A possible explanation for this difference is that 1-day annual maxima usually pertain to the warm season, whereas our study is restricted to precipitation extremes in the cold season. Geographic variability in the spread of the changes in precipitation in the GCM simulations could be another reason for the differences between our results and those of Brekke and Barsugli (2013) for the 1-day annual maxima in the US.

The large influence of internal climate variability on the changes in extremes is a source of concern for developers of climate change scenarios for impact modelling. Kay et al. (2009) concluded that understanding natural variability is critical in assessing the importance of climate change impacts on hydrology. Because of natural variability, the spread of the changes in an ensemble of climate model simulations generally overestimates the uncertainty of the true human induced climate change signal. A challenging task is to develop climate change scenarios representing only the climate-model and greenhouse-gas emission uncertainties.

Surprisingly, the variance due to internal climate variability turned out to be smaller for the change in $P_{90}$ than for the change in the average winter precipitation. This implies in fact that a change in $P_{90}$ over the Rhine basin can be easier detected than a change in the long-term mean. Note that this phenomenon may depend on the scale of the region because the effect of spatial pooling on the variance of the change in $P_{90}$ may be different from that on the variance of the change in the average winter precipitation. The effect of spatial pooling also depends on geography and the season of interest. Our result is in accordance with Räisänen and Joelsson (2001) who observed that the internal climate variability of the 1-day annual maximum precipitation is reduced stronger at larger spatial scales than the internal climate variability of the annual mean precipitation, and with Hegerl et al. (2004) who, noted that changes in moderately extreme precipitation should be better detectable than changes in the annual mean precipitation because of a greater consistency between the change patterns in these extremes in climate model simulations.

Ultimately, the discrimination between internal climate variability and model uncertainty in this study is quite inaccurate owing to the limited ensemble size. Especially the standard error of the interexperiment variance $V$ turned out to be large. Larger ensembles are needed to distinguish model uncertainty in the changes of extreme precipitation characteristics well from internal climate variability. Ensembles with multiple runs of each GCM could also be useful. Averaging over these runs reduces the influence of internal climate variability. Kendon et al. (2008) and Kew et al. (2011) advocated the use of multiple runs to improve the detection of changes in moderately extreme precipitation.



The influence of internal climate variability can also be reduced by spatial and temporal smoothing. Kendon et al. (2008) point out that spatial smoothing is, however, much less effective than analysing multiple runs. Moreover, in the present study the exponent $b$ and the relative change in $\overline{E}_{90}$ were taken constant over the Rhine basin. It has further been shown that the effect of temporal smoothing on the spread of the relative changes during the winter half-year is small (Van Pelt et al. 2012). For the estimation of the changes in $\overline{E}_{90}$ in particular, it may be worthwhile to consider a longer time slice for the future climate than the 20-year period in the present study.

The estimates of the return levels of 10-day precipitation and discharge were based on 3,000-year synthetic sequences of daily precipitation and temperature. Despite the length of these sequences the uncertainty of extreme events (either 10-day precipitation or river discharge), with return periods as large as 1,000 years, is high, owing to the short record of historical observations used as the basis for resampling. Also, the assumption is made, that there is no change in the shape of the right tail of the distribution, which may lead to substantial systematic errors. The method followed in this study is, however, currently one of the best options available to estimate (changes in) return levels associated with long return periods. Even though the uncertainties are high, the knowledge about changes in extremes is very relevant for the development of adaptation measures for our safety system, which is designed to withstand long-return period events.

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# Chapter 5

# Including climate change projections in probabilistic flood risk assessment

This chapter has been published as:
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# Abstract

This paper demonstrates a framework for producing probabilistic flood risk estimates, focusing on two sections of the Rhine River. We used an ensemble of six (bias-corrected) regional climate model (RCM) future simulations to create a 3,000-year time-series through resampling. This was complemented with 12 global climate model (GCM)-based future time-series, constructed by resampling observed time-series of daily precipitation and temperature and modifying these to represent future climate conditions using an advanced delta change approach. We used the resampled time-series as input in the hydrological model Hydrologiska Byråns Vattenbalansavdelning (HBV)-96 to simulate daily discharge and extreme discharge quantiles for return periods up to 3,000 years. To convert extreme discharges to estimates of flood damage and risk, we coupled a simple inundation model with a damage model. We then fitted probability density functions (PDFs) for the RCM, GCM, and combined ensembles. The framework allows for the assessment of the probability distribution of flood risk under future climate scenario conditions. Because this paper represents a demonstration of a methodological framework, the absolute figures should not be used in decision making at this time.

## 5.1 Introduction

To date, future flood risk assessments have predominantly relied on a discrete scenario-based approach (IPCC, 2007). This is also the case in climate change assessments in general. Recent research proposes a probabilistic approach, generating probability density functions (PDFs) of climate change, (e.g. Rougier, 2007; Tebaldi, Mearns, Nychka, & Smith, 2004). Potentially, large ensembles of global climate model (GCM) and regional climate model (RCM) simulations could provide more information on risk and uncertainty than using a limited number of discrete scenarios (New, Lopez, Dessai, & Wilby, 2007). The climate impacts community has also expressed the need for probabilistic impact assessments, (e.g. Pittock, Jones, & Mitchell, 2001; Reilly et al., 2001; Webster, 2003). Examples of probabilistic climate impact studies exist in several fields, including global crop yields (Tebaldi & Lobell, 2008), water resource management (Manning, Hall, Fowler, Kilsby, & Tebaldi, 2009; New, et al., 2007), and storm surges (Gaslikova, Schwerzmann, Raible, & Stocker, 2011). A probabilistic flood risk study is that of Apel et al. (2006), in which a simple stochastic approach allowing a large number of simulations in a Monte Carlo framework provided the basis for a probabilistic risk assessment for an area of the Rhine (between Cologne and Rees, with a focus on the polder at Mehrum). Apel et al. (2008) extended this work to a risk assessment of the lower Rhine including an uncertainty analysis. However, while these studies examine probabilistic risk assessments based on current climate observations, they do not develop scenarios of flood risk under future climate change. In our study we describe a first assessment.



A probabilistic flood risk assessment considers the chain between climate, hydrological discharge, inundation, and impact. Each component of this chain is associated with a probability distribution (represented by a large number of ensemble members or scenarios), and the range of possibilities quickly increases during the descent down this chain. A severe limitation in this approach is the seemingly unlimited number of inundation maps required: for each ensemble member and/or scenario, damage estimates must be generated for several flood return periods, each with a different associated inundation depth and extent. Generally, the production of flood hazard maps is time consuming and expensive (Apel, et al. 2008; Woodhead et al., 2007). Hence, inundation models are required that are capable of rapidly simulating inundation extent and depth. For this research, we therefore used a simple flood inundation model and coupled it to an existing flood damage model. We use the definition of flood risk being a function of hazard, exposure, and vulnerability, (e.g. Chrichton, 1999; UNISDR, 2011). In this paper, we express risk in terms of the annual expected damage.

The main aim of this paper is to provide a demonstration of a framework for producing probabilistic estimates of future flood risk and to demonstrate how ensembles of climate projections can be used for this purpose. Because this paper represents a demonstration of a methodological framework, the absolute figures should not be used in decision making at this time.

## 5.2 Study area and related publications

The research focuses on flood risk in two case-study stretches of the River Rhine in Germany: Mainz-Koblenz and Bonn-Duisburg (see Figure 5.1). The Rhine originates in the Swiss Alps as a mountain river, fed by glacier water, snowmelt, and rainfall. From Switzerland it flows through Germany, France, and the Netherlands into the North Sea. About 58 million people inhabit the river basin, of whom an estimated 10.5 million live in flood-prone areas (ICPR, 2001).

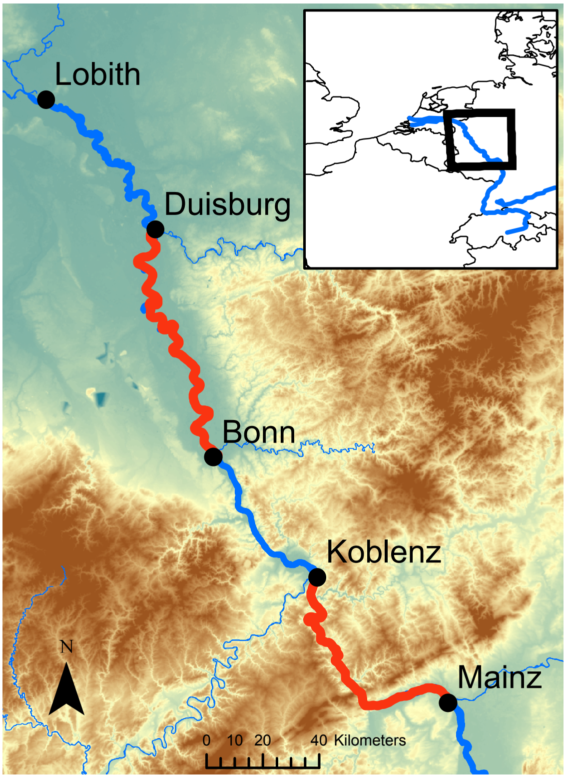


**Figure 5.1.** Map of the two case-study locations; which are shown in red.

Many studies have assessed how climate change may alter the discharge regime of the Rhine, see (Görgen, et al., 2010; Te Linde, et al., 2010). These studies suggest that mean winter discharge at Lobith (at the border of Germany and the Netherlands; Figure 5.1) may increase by 0–30% by 2050 and that the magnitude of extreme flood events is likely to increase. However, for the Rhine basin the assessment of flood risk is still in its early phases. The International Commission for the Protection of the Rhine used the Rhine Atlas approach to estimate aggregated flood damage for the whole basin (ICPR, 2001), but: (1) it yields rather low potential damage values for different land use classes compared with other studies,(e.g. Moel & Aerts, 2011); and (2) it does not differentiate between different urban classes, while such a differentiation is essential for flood damage estimates (Apel, Aronica, Kreibich, & Thieken, 2009). Recently, Te Linde et al. (2011) and Bubeck et al. (2011) estimated flood risk using the Damagescanner model (Klijn, Baan, De Bruin, & Kwadijk, 2007), but only assessed the damage for one return period and did not perform a probabilistic analysis. Apel et al. (2006) developed a stochastic approach for probabilistic risk estimates under current conditions for a section of the Rhine, with a focus on the polder at Mehrum, and Apel et al. (2008) extended this work to a risk assessment of the lower Rhine between Cologne and the German–Dutch border.

## 5.3 Methods and data

The overall approach can be broken down into the following steps: (1) generating long (3,000-year) climate time series; (2) generating long (3,000-year) discharge time-series; (3) estimating discharge values for low probability floods; (4) simulating flood inundation extent and depths as a function of return period; (5) estimating flood damage; and (6) estimating flood risk and probability distributions of flood risk. In the following sections we summarise each of these steps (more detailed descriptions can be found in Ward et al. (2011)).



### 5.3.1 Generating long (3,000-year) climate time-series

We used 18 daily time-series of precipitation and temperature, representing climate conditions at the end of the 21$^{st}$ century; 12 were based on transformed GCM simulations, and six were based on bias-corrected RCM simulations. Each of the time-series was used to force a hydrological model with a daily time-step. In this section, we summarise the main steps. The overall approach for generating the 3,000-year climate time-series is shown in Figure 5.2. A detailed description can be found in Ward et al. (2011a) and Van Pelt et al. (2012).

An ensemble of six bias-corrected, resampled time-series of 3,000 years from RCM simulations was made available through the RheinBlick2050 project (Görgen, et al., 2010). The 3,000-year bias-corrected future RCM time-series were constructed by applying a non-linear bias correction to the 3,000-year resampled future RCM time-series. The bias correction was carried out based on an observed time-series. The observed time-series used was a 35-year time-series of precipitation and temperature from the International Commission for the Hydrology of the Rhine Basin (CHR). These observations contain area-averaged daily precipitation and temperature for 134 sub-basins of the Rhine, for the period 1961–1995. Some of these RCM simulations were forced by different versions or runs of the same GCM. In order to enlarge the number of GCMs in our ensemble, 12 GCM simulations run in the context of the third Coupled Model Intercomparison Project were added using an advanced delta change approach (Pelt, et al., 2012; Ward, Aerts, et al., 2011). The models used are listed in Table 5.1. For both the GCM and RCM simulations, a single greenhouse gas emission scenario was used, namely the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios A1B scenario.

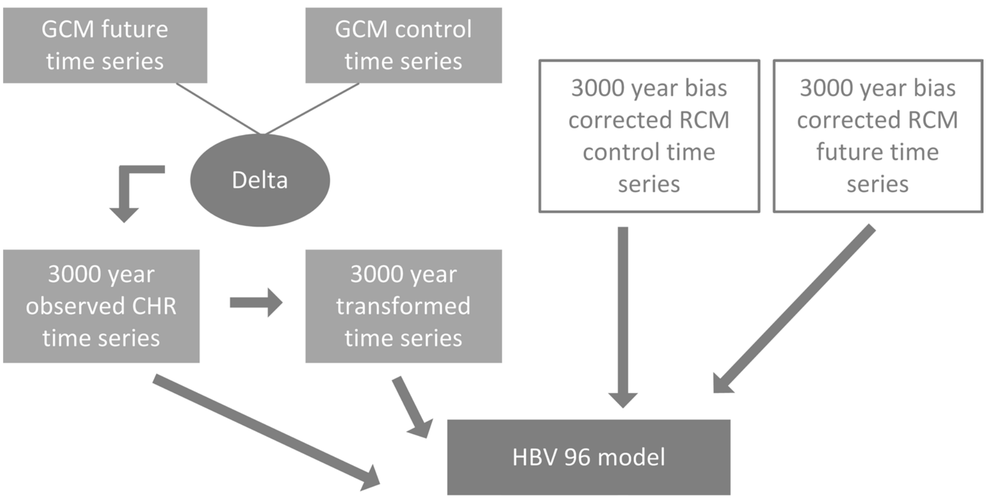


**Figure 5.2.** Flow chart showing the main steps taken to produce the 3,000-year climate time-series

We used daily time-series from 12 GCMs for a control period of 35 years (1961–1995) and a future period of 20 years (2081–2100). The GCM control and future time-series were used to obtain the deltas needed in the advanced delta change method, as shown in Figure 5.2. These deltas were then applied to a (resampled) 3,000-year observed time-series to obtain a 3,000-year time-series representative of the future climate. The resampled 3,000-year observed time-series (of daily precipitation and temperature) were derived by Beersma (2001) from the observed 35-year CHR time series of precipitation and temperature. The resampling algorithm used in this study can be regarded as a non-parametric weather generator. Its details, development, and applications are largely described in Buishand and Brandsma (2001), Leander et al. (2005) and Görgen et al.(2010).

In the advanced delta change method, the delta for precipitation consists of using the non-linear transformation introduced in Leander and Buishand (2007):

$$P^* = aP^b \tag{5.1}$$

where $a$ and $b$ are the transformation coefficients used to scale the observed precipitation ($P$) to a future precipitation ($P^*$). The coefficients $a$ and $b$ are derived from the GCM control and future simulations (for details see Van Pelt et al., 2012).

The delta for temperature corresponds to a transformation of observed daily temperature ($T$) to a future daily temperature ($T^*$):

$$T^* = \frac{\sigma^{\mathrm{F}}}{\sigma^{\mathrm{C}}} * \left(T - \bar{T}^{\mathrm{C}}\right) + \bar{T}^{\mathrm{F}} \tag{5.2}$$

where $\sigma^{\mathrm{F}}$ is the daily temperature standard deviation in the GCM future climate simulation and $\sigma^{\mathrm{C}}$ that in the GCM control simulation. Similarly, $\bar{T}^{\mathrm{F}}$ and $\bar{T}^{\mathrm{C}}$ are the mean temperatures in the GCM future and control simulations, respectively.

In summary, the 3,000-year transformed time-series are created using the climate change (delta) in each GCM. The RCM-based climate time-series, on the other hand, were constructed by applying a non-linear bias correction to 3,000-year resampled control and future RCM time-series. Note that for the RCMs, each future simulation has its own reference (i.e. control) simulation, while the transformed observed time-series all have the same reference simulation (i.e. the observed time-series).

### 5.3.2 Generating long (3,000-year) discharge time-series

The hydrological model used to generate daily discharge time-series is HBV-96. It is a conceptual model divided into 134 sub-basins for the entire Rhine Basin upstream from Lobith and has a daily time-step (Eberle, Buiteveld, Krahe, & Wilke, 2005; Te Linde, Aerts, Hurkmans, & Eberle, 2008). A detailed description of the calibration of the model can be found in Görgen et al. (2010). In brief, it is calibrated and validated for different periods within the period 1961–1999, depending on available data in each part of the river basin. Validation results for the main gauging stations in the Rhine River show Nash–Sutcliffe coefficients above 0.9, although the 1993 and 1995 floods events are overestimated by more than 10% at the border of Germany and the Netherlands. A recent comparison of observation-based and model-based flood statistics shows differences of less than 5% for the lower part of the Rhine river for return periods between 10 and 1,000 years (Görgen, et al., 2010).

In this study, HBV-96 was forced with the 3,000-year climate time-series described earlier. A validation of discharge computed from the bias-corrected control RCM simulations was applied by comparing discharge values calculated with the CHR data as input; details can be found in Görgen et al. (2010). For the middle and lower parts of the Rhine Basin, which are part of this case study, these simulations reproduced the observed flood statistics well. It is important to mention that no hydrodynamic modelling was performed, so the effects of flood plain attenuation upstream on discharge (and inundation) downstream are not considered.

### 5.3.3 Estimating discharge values for low probability floods

The river stretches of the Rhine considered in this study are protected against floods with a return period of approximately 200 years. Hence, we only considered discharge events with a return period in excess of 200 years for the inundation scenarios and damage estimates. From the 3,000-year synthetic discharge time-series, we took the annual maximum discharge for each hydrological year (November–October) per ensemble member. We then estimated extreme discharge by fitting a distribution to the 15 largest values using the Weissman (1978) approach, which is based on the joint limit distribution of the $k$ largest order statistics. This method provides more consistent results than fitting a generalised extreme value (GEV) distribution to the whole data series because of the relatively strong influence of low values on the estimated upper quantiles of the distribution in the latter approach.

### 5.3.4 Simulating flood inundation extent and depths

The methodological framework used in this study requires the simulation of hundreds to thousands of maps showing inundation extent and depth. Given the large number of simulations needed for our probabilistic framework, we used the simple Floodscanner approach, described in Ward et al. (2011). Floodscanner uses a zero-dimensional planar-based approach, conceptually similar to that described in Priestnall et al. (2000). Floodscanner is raster based, with a horizontal resolution of 50 m × 50 m. In brief, the method uses stage–discharge relationships to estimate water level at each river grid-cell for different discharges. These water levels are then assigned to the nearest non-river grid-cells, creating a planar surface representing the water level per grid-cell. This planar water level is then intersected with a digital elevation model (DEM), and the inundation depth is the difference between the cell values of water level and elevation. Several steps are required: (1) derive river network raster; (2) develop stage–discharge relationships; (3) simulate planar water-level surface; and (4) estimate flood inundation depth.

*(1) Derive river network raster*: We extracted the river network raster from the Shuttle Radar Topography Mission (SRTM) DEM (Jarvis, Reuter, Nelson, & Guevara, 2006). The DEM has a horizontal resolution of 90 m × 90 m and was regridded to the higher resolution of 50 m × 50 m. Ideally, a DEM with higher horizontal resolution and accuracy would be used, but such a DEM was not available.
*(2) Develop stage–discharge relationships*: For this study we used stage–discharge ($Q$–$h$) data from the SOBEK model described by Te Linde et al. (2011). This one-dimensional (1D) SOBEK model schematisation describes the main Rhine Channel and contains the geometry of the cross-sections at every 500 m. The model is calibrated by tuning bed friction values (Van der Veen, 2007). Floods are schematised by large retention polders with regulated inlet and outlet structures. The inflow and outflow locations and discharge volumes of flood events are based on several two-dimensional (2D) hydrodynamic flood simulations with a model called Delft flooding system (FLS), which contains the geometry of the river valley (Van der Veen, Lammersen, Kroekenstoel, & Brinkmann, 2004). As a result, the $Q$–$h$ relationships of the 1D SOBEK model and 2D

Delft FLS model are the same. The data show the river stage (*h*) corresponding to 30 discharge values (*Q*) at irregular distances along the river, ranging from ca. 0.5 km to 1.0 km. Floodscanner assigns these values to the correct river grid-cell in the river network raster and then estimates values for each intervening river cell through linear interpolation. For each river cell, a *Q*–*h* relationship is then derived (showing the *h* at each river grid-cell corresponding to the *Q* at a given input river cell, see next step).
*(3) Simulate planar water-level surface*: For the two sections studied in this research, i.e. Bonn-Duisburg and Mainz-Koblenz, the discharges at Cologne and Kaub, respectively, are given to the model as input, and the corresponding water level at each river grid-cell is calculated based on the *Q*–*h* relationships. All grid-cells are assigned to their nearest river grid-cell based on Euclidean distance, resulting in a theoretical planar water-level surface.
*(4) Estimate flood inundation depth*: The elevation of each grid-cell is subtracted from the planar water-level surface to give a theoretical inundation depth per grid-cell. Finally, inundated cells not connected to the river via a flow path with direct connectivity (in at least one of eight directions) are removed. No hydrodynamic model was used, so it is assumed that upstream flooding does not lead to a reduction in discharge downstream. Moreover, the zero-dimensional planar-based approach does not contain a volumetric control. These two factors may lead to an overestimation of downstream inundation depths, especially in regions with very flat floodplain topographies.

The model has previously been tested for a section of the neighbouring Meuse basin in Dutch Limburg, performing well compared with images of the historical floods of 1993 and 1995, as well as compared with results from a process-based 2D hydrodynamic model (WAQUA) (Ward, de Moel, et al., 2011), and the results for the Rhine have been compared with several other studies in Ward et al. (2011). The simplifications used in the approach do not allow flood damage estimates at fine resolutions (e.g. street to city scale), which need state-of-the-art hydraulic modelling methods,(e.g. Ernst et al., 2010). Our approach is intended to be complementary to such methods for use in regional-to-basin scale studies in which large numbers of inundation maps are required.



### 5.3.5 Estimating flood damage

We calculated potential direct economic damage for each inundation scenario using the Damagescanner model (Klijn, et al., 2007). Damagescanner has been described in several studies (Bouwer, Bubeck, & Aerts, 2010; Te Linde, et al., 2011). It requires two inputs: a land use map and an inundation map. The land use map (year 2000) was derived from the Landuse scanner model (Hilferink & Rietveld, 1999) for the Rhine (Te Linde, et al., 2011). The inundation maps were derived from Floodscanner. Damagescanner combines information on land use and inundation depth using depth-damage functions, which estimate the expected damage for a given inundation depth and a given land use (different curves) for each grid-cell. The absolute depth-damage functions used in this study are those described in Te Linde et al. (2011) and Ward et al. (2011).

### 5.3.6 Estimating flood risk and probability distributions of flood risk

Economic risk, here expressed as expected annual damage, can be considered as the area under an exceedance probability-damage curve (risk curve). In practice, the number of exceedance probabilities used to develop such a curve is limited by available computer and manpower resources. Ward et al. (2011) have shown that estimates of flood risk are strongly affected by the choice of exceedance probabilities used to develop the risk curve. In this research we assessed losses associated with return periods between 200 and 3,000 years (i.e. exceedance probabilities between 0.005 and 0.00033, with a step of 10 years). We assumed no damage to occur at flood levels for return periods shorter than 200 years because the case-study regions are protected against floods with more frequent return periods. A risk curve was developed for the reference climate (resampled CHR dataset, corresponding to 1961–1995) and for the future climate for each GCM/RCM ensemble member (corresponding to end of the 21$^{st}$ century, ca. 2081–2100). Risk was calculated for each ensemble member as the area under the risk curve; the change in risk between current and future conditions was calculated for each ensemble member in relation to the risk estimate for the CHR reference dataset. In a final step, we fitted PDFs to the estimates of risk from each of the climate model runs. Although it is not our goal to carry out a full uncertainty analysis on future flood risk, the epistemic uncertainty associated with the use of the different climate model input data is presented in terms of PDFs and confidence intervals.

## 5.4 Results and Discussion

### 5.4.1 Hydrological model simulations

In order to assess possible future changes in discharge compared with present day, Figure 5.3 shows the mean annual maximum discharge (MHQ) and the 200- and 1,000-year discharges (HQ200 and HQ1000, respectively) at Cologne and Kaub. A thorough analysis of the reference values resulting from the CHR dataset (as well as the control runs of each RCM) is described in Görgen et al. (2010). In general, the (resampled) time-series representing the future conditions tend to show an increase in the estimated quantiles of average and extreme discharge compared with the (resampled) CHR reference dataset. These increases are generally greater for the GCM ensemble compared with the RCM ensemble. Still, there are also several ensemble members that project a decrease in flood discharges. We also found interesting spatial differences between the discharge simulations forced by different climate model data. For example, at Kaub, the highest HQ1000 is for the MIUB GCM, whereas at Cologne the HADCM3Q0 GCM is the highest. For the latter, the estimated HQ1000 (ca. 22,282 $m^3s^{-1}$) is somewhat lower than the peak simulation of Te Linde et al. (2010) of 25,110 $m^3s^{-1}$ at Lobith (border Germany–the Netherlands). They used the

RACMO RCM and GEV fit to obtain low probability discharge estimates. The MIUB GCM simulates much wetter conditions in the river basin upstream from Kaub, while the HADCM3Q0 GCM simulates the wettest conditions in the lower part of the basin and the Mosel River Basin. Hence, the climate model ensemble members do not cause the same changes in extreme discharge in all parts of the basin. This demonstrates the importance of using spatially distributed climate simulations when carrying out climate change impact studies.

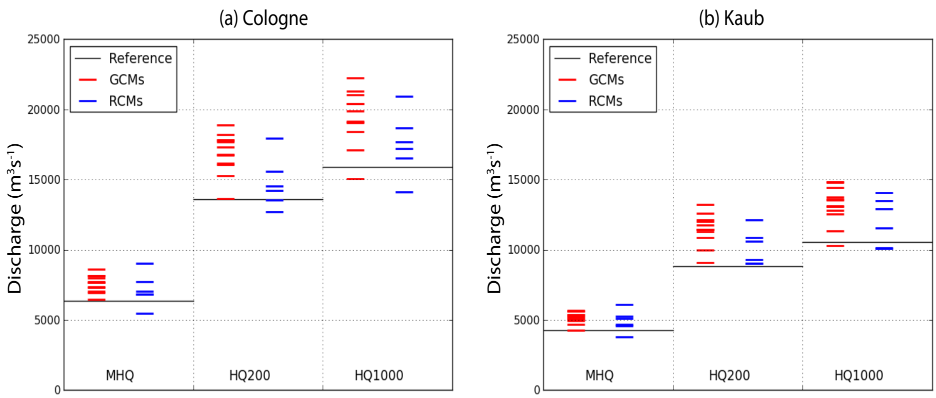


**Figure 5.3.** Plots for (a) Cologne and (b) Kaub of projected: mean annual maximum discharge (MHQ), and 200- and 1,000-year discharges (HQ200 and HQ1000). Global climate model (GCM) members are shown in red and regional climate model (RCM) members in blue (both representing future conditions around the end of the 21st century). The black lines denote the discharge for the International Commission for the Hydrology of the Rhine Basin (CHR) reference dataset (1961–1995).

### 5.4.2 Probabilistic flood risk assessments

We developed a risk curve for each (future) RCM and GCM ensemble member, and for the (resampled) CHR reference dataset, assuming no damage to occur at flood levels for return periods shorter than 200 years (Figure 5.4). The risk curve is based on damage estimates associated with flood return periods between 200 and 3,000 years. Extending the risk curves to include damage estimates associated with flood return periods up to 10,000 years led to an increased risk by ca. 10% for Bonn-Duisburg and ca. 8% for Mainz-Koblenz. However, for this project we present the results based on the damage estimates up to 3,000 years because the Weissman parameters were estimated based on a synthetic time-series of 3,000 years. Results per ensemble member are shown in Table 5.1, and several key statistics of each ensemble can be found in Table 5.2. The range between the maximum and minimum risk estimate is slightly larger in the GCM ensemble than in the RCM ensemble for both case-study areas, although the standard deviation is smaller. However, the differences between both ensembles are small and may be partly related to the difference in ensemble size. While one of the highest risk estimates is for the HADCM3Q0 GCM simulation (as this ensemble member represents very wet conditions), the RCM simulation HADCM3Q0-CLM (i.e. CLM forced by the HADCM3Q0 GCM) results in one of the lowest risk estimates (as it is one of driest ensemble members). Hence, the RCMs used in this study have a strong influence on the risk estimates. Next to total expected annual risk, we show annual expected risk per capita (Table 5.1), calculated using LandScan (2008) data, to estimate the number of people living in the area exposed to the 3,000-year return period flood. While the total expected annual risk is higher for the section Bonn-Duisburg – because the inundation extent in this area is much larger than for Mainz-Koblenz – the annual expected risk per capita is lower .

**Table 5.1.** Annual risk and annual risk per capita for the two case-study regions per climate simulation

| | Bonn-Duisburg | | Mainz-Koblenz | |
|---|---|---|---|---|
| Climate simulation | Annual risk (€ million) | Annual risk per capita (€) | Annual risk (€ million) | Annual risk per capita (€) |
| Reference (1961-1995) | 60.3 | 46 | 5.1 | 77 |
| *RCMs* | | | | |
| ARPEGE; HIRHAM5 | 70.9 | 54 | 5.8 | 88 |
| ECHAM5R1; REMO | 42.6 | 32 | 5.1 | 78 |
| ECHAM5R3; RACMO | 145.9 | 110 | 9.0 | 136 |
| ECHAM5R3; REMO | 99.8 | 76 | 7.7 | 116 |
| HADCM3Q0; CLM | 69.3 | 52 | 5.0 | 75 |
| HADCM3Q3; HADRM3Q3 | 82.2 | 62 | 7.8 | 118 |
| *GCMs* | | | | |
| CCCMA | 115.0 | 87 | 8.3 | 125 |
| CNRM | 121.9 | 92 | 8.4 | 126 |
| CSIRO | 82.2 | 62 | 6.2 | 93 |
| ECHAM5 | 54.2 | 41 | 5.1 | 77 |
| GFDL 2.0 | 101.0 | 76 | 7.5 | 113 |
| GFDL 2.1 | 148.7 | 113 | 9.1 | 138 |
| HADCM3Q0 | 170.4 | 129 | 9.7 | 146 |
| HADCM3Q3 | 133.3 | 101 | 8.5 | 128 |
| IPSL | 128.9 | 98 | 8.3 | 125 |
| MIROC | 109.3 | 83 | 7.9 | 120 |
| MIUB | 142.8 | 108 | 10.0 | 151 |
| MRI | 144.9 | 110 | 8.5 | 128 |

Figure 5.4. shows that the risk curves for individual ensemble members cross each other at many points. In other words, the ranking of the damage for the different ensemble members is not constant for different return periods. Hence, the ranking of risk between different ensemble members is strongly affected by the part of the curve used to estimate risk. This supports recent findings by Ward et al. (2011b) showing that estimates of risk are strongly dependent on the choice of return periods used to estimate risk.

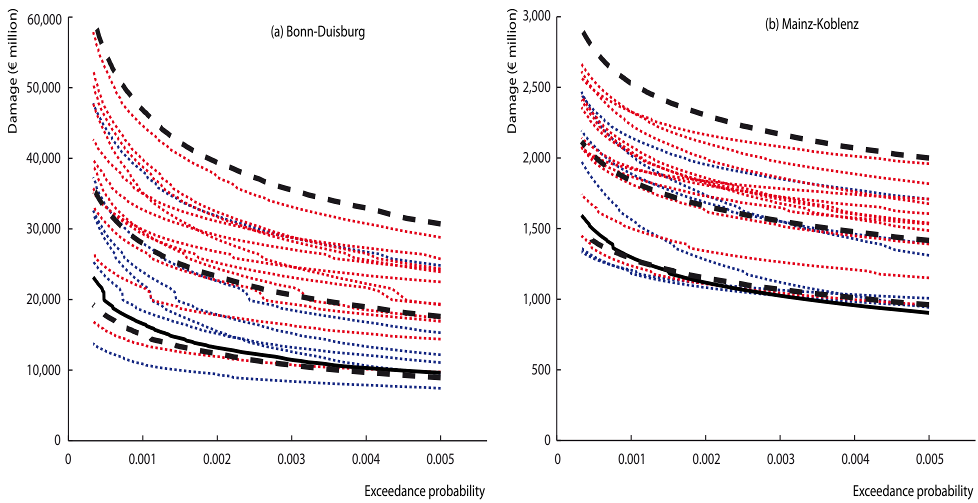


**Figure 5.4.** Risk curves for: (a) Bonn-Duisburg and (b) Mainz-Koblenz. The solid black line shows the risk curve for the International Commission for the Hydrology of the Rhine Basin (CHR) reference dataset. Risk curves for future regional climate model (RCM) ensemble members are shown in blue and for future global climate model (GCM) ensemble members in red. Black dashed lines show average and 5% and 95% percentiles of a two-parameter gamma distribution fit to all members of the full future model ensemble. The future risk curves represent the situation at the end of the 21st century.

**Table 5.2.** Key statistics related to the (future) expected annual risk (€ million per year) for the regional climate model (RCM), global climate model (GCM), and full ensembles.

| | Bonn-Duisburg | | | Mainz-Koblenz | | |
|---|---|---|---|---|---|---|
| | RCM ensemble | GCM ensemble | Full ensemble | RCM ensemble | GCM ensemble | Full ensemble |
| Maximum | 145.9 | 170.4 | 170.4 | 9.0 | 10.0 | 10.0 |
| Minimum | 42.6 | 54.2 | 42.6 | 5.0 | 5.1 | 5.0 |
| Range | 103.3 | 116.2 | 127.7 | 4.0 | 4.9 | 5.0 |
| Mean | 85.1 | 121.0 | 109.1 | 6.7 | 8.1 | 7.7 |
| St. dev. | 35.1 | 31.6 | 36.3 | 1.7 | 1.4 | 1.6 |

In Figure 5.5, the PDFs of future flood risk are shown. We applied a two-parameter gamma distribution to the risk estimates from each member in each ensemble (RCM, GCM, and combined, i.e. full ensemble), whereby each ensemble member was assumed to have an equal probability (i.e. no weighting was applied). The average and 5% and 95% percentiles of the gamma distribution are also shown on the risk curves in Figure 5.4. The addition of the GCM ensemble to the existing RCM ensemble from RheinBlick2050 leads to an increase in the spread of the PDF of the full ensemble.

Within the context of this demonstration study, the probabilistic risk assessment approach allows us to estimate the change in the probability of flood risk (compared with current conditions) assuming the A1B emission scenario. The probability that the future flood risk exceeds the current risk is 92% for the section Bonn-Duisburg and 96% for the section Mainz-Koblenz. Moreover, the probability of future flood risk exceeding twice the current risk is 34% for Bonn-Duisburg and 6% for Mainz-Koblenz. By extension, it is possible to assess the probability that flood risk will increase by any given factor, allowing for the assessment of risk under possible extreme futures.

The order of magnitude of the estimated flood damage for a flood with a return period of 1,000 years for the reference period is the same as that simulated by Apel et al. (2008) for the section of the Rhine from Cologne to close to the German–Dutch border. In our study, we estimate this damage as ca. €17,000 million. Apel et al. (2008) estimate this damage under several sources of uncertainty, with the average estimate being ca. €22,000 million when a 35-year observed annual maximum discharge time-series was used (with the 2.5% and 97.5% percentiles being ca. €0 and ca. €40,000 million, respectively) and ca. €17,000 million when a 1,000-year synthetic annual maximum discharge time-series was used.

A recent study by Te Linde et al. (2011) examined flood risk for the entire Rhine Basin for a reference year 2000 and two climate change scenarios for 2030. The scenarios were derived using different methodologies (Te Linde et al., 2010) and are labelled as ‘extreme’ and ‘moderate’. Increases in basin-wide flood risk between 2000 and

2030 were calculated to be 43% (moderate) and 161% (extreme). Results from our demonstration study suggest that the probability of flood risk increasing by 43% in 2090 is 67% for Bonn-Duisburg and 55% for Mainz-Koblenz, while the probability of flood risk increasing by 161% by 2090 is 11% for Bonn-Duisburg and only 0.1% for Mainz-Koblenz. A comparison with results of Te Linde et al. (2011) is limited by: (1) the use of different methods to calculate risk; (2) the choice of a different analysis period; and (3) a different areal aggregation level. However, these limitations notwithstanding, the extreme risk estimate of Te Linde et al. (2011) is indeed at the upper tail of our results.

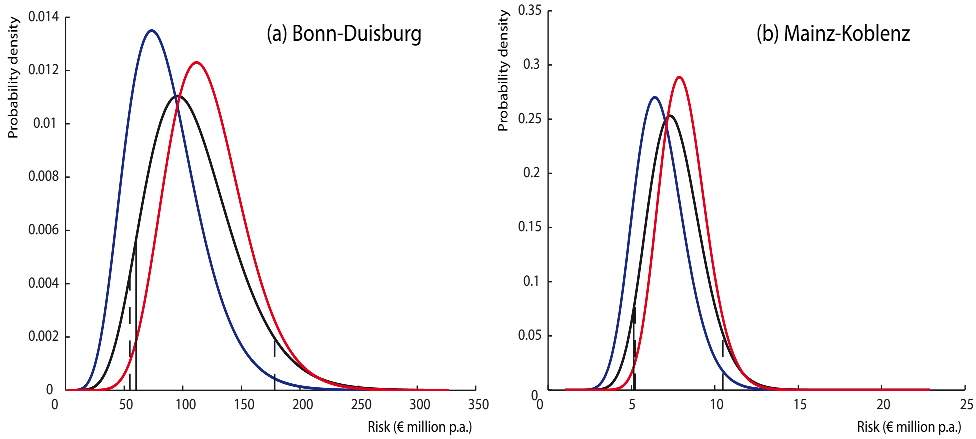


**Figure 5.5.** Probability distribution of flood risk for: (a) Bonn-Duisburg and (b) Mainz-Koblenz. The black vertical solid line shows the risk associated with current climate conditions (based on the resampled International Commission for the Hydrology of the Rhine Basin (CHR) reference dataset (1961–1995)). Curves show the risk probabilities derived from the regional climate model (RCM) ensemble (blue), global climate model (GCM) ensemble (red), and full ensemble (i.e. all members of the RCM and GCM ensembles). Distributions are obtained by applying a two-parameter gamma distribution. Vertical dashed lines show the 5% and 95% percentiles of the distribution of the full future ensemble.

Such probabilistic information could help insurers and reinsurance companies in computing insurance premiums under uncertainty (Michel-Kerjan, 2008) and deriving the amounts of capital reserves required for potential damage reimbursements. Our results also illustrate how spatially differentiated estimates of risk per capita can be developed. For example, our demonstrative analyses suggest that while the total annual risk is higher for the section Bonn-Duisburg than for Mainz-Koblenz, the annual risk per capita is lower. Information about extreme risk is also relevant for decisions concerning the hedging of the tails of the loss distribution on reinsurance or capital markets (Froot, 1999); the tails of the flood risk PDFs could assist in such assessments. In cases where governments (partly) compensate for the flood damages (like in the Netherlands), the framework can also provide information to governments about their financial risk exposure (Grossi & Kunreuther, 2006).

### 5.4.3 Limitations and recommendations

This study is a demonstration of the methodological steps needed to assess future flood risk under climate change in a probabilistic framework. While the ensemble of climate model simulations used here contains more members than past research on future flooding, its size (18 members) still makes the selection of a theoretical distribution to describe the PDF of risk difficult (Hall, 2007; New, et al., 2007; Rougier, 2007). Also, it is unknown to what extent the ensemble members can be considered to be independent and how many degrees of freedom are required to adequately quantify risk estimates. We did not assign weights to individual model members in this study. Theoretically, a weighting could be given to each GCM/RCM simulation based on its ability to realistically downscale observed climate for the reference period. However, models that reproduce the past climate are not necessarily those that will give the most realistic realisation of the future.

The demonstration study does not represent several major sources of uncertainty (e.g. Merz et al, 2010). Firstly, uncertainty emerging from the range in future emission estimates is not included (we only use the A1B scenario). Secondly, one realisation per climate model was used for most models, and so the influence of natural variability may be underrepresented, while natural climate variability has a large influence on extreme river discharges (Ward, Beets, Bouwer, Aerts, & Renssen, 2010). Thirdly, the RCM simulations have been bias-corrected, and it is assumed that the same correction applies to the control and future simulations. Finally, we did not address the considerable uncertainty in both the hydrological and inundation models. Future studies should elucidate the magnitude and importance of these sources of uncertainty.

Finally, in this paper we examined the influence of climate change on future hazard, leaving future exposure and vulnerability unchanged. However, several studies (Jongman, Ward, & Aerts, 2012; Te Linde, et al., 2011) have shown that the impacts of the latter elements on overall risk are also substantial, if not greater than the impact of climate change. Hence, future studies should aim to develop methods for including future changes in exposure and vulnerability using a probabilistic framework.

## 5.5 Concluding remarks

We present a first attempt to assess future flood risk under climate change in a probabilistic framework. It is not sufficient to estimate damage for just a handful of return periods because the risk curves for individual ensemble members cross each other at many points. In other words, the ranking of risk between different ensemble members is strongly affected by the part of the curve chosen to estimate risk. Hence, the availability of rapid inundation models is essential in a probabilistic flood risk modelling framework. The method applied here is capable of this, but refinements are essential to include the most important physical processes in a simple manner.

We developed probabilistic flood risk scenarios for two case-study sections of the Rhine. Our analyses allow the estimation of the probability that future flood risk exceeds current risk (given the limitations of the study). By extension, using such a framework it is possible to assess the probability that flood risk will increase by any given factor, allowing for the assessment of risk under possible extreme future situations. The research shows that the addition of the GCM ensemble to the existing RCM ensemble from RheinBlick2050 leads to a slightly wider distribution of future flood risks estimates. However, the spread of the individual RCM and GCM ensembles is rather similar.

This study illustrates an interesting feature of the probabilistic framework explored here: it allows the evaluation of a discrete scenario in the context of a wider probability distribution. Future research into where the results of such discrete scenarios fit into probabilistic flood risk estimates would provide an interesting research avenue. Moreover, it demonstrates that results from individual or discrete model simulations should be treated with care.

The research is intended to give a demonstration of the methods that can be used in a probabilistic flood risk framework; the absolute figures should not be used in decision making at this time. Probabilistic flood risk assessments hold promise, but research remains to be carried out to: refine the methods presented here; examine how the methods can be applied to improve adaptation planning; assess how decision makers use results of probabilistic impacts assessments; and to investigate how the information provided can most effectively be communicated to stakeholders.



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# Chapter 6

# Communicating climate (change) uncertainties: simulation games as boundary objects

This chapter has been submitted as:
Van Pelt, S.C. Haasnoot, M., Arts, B.J.M., Ludwig, F., Swart, R.J., & Biesbroek, G.R. Communicating climate (change) uncertainties: simulation games as boundary objects. *Environmental Science and Policy.*

# Abstract

Climate science is characterized by large uncertainties about the direction, extent and time frame of climate change. Communicating these uncertainties is important for decision making on robust adaptation strategies, but proves to be a challenge for scientists particularly because of the complexity of uncertainties that are part of natural variability and of human induced climate change. The aim of this paper is to assess the role of a simulation game, as intermediate, to the communication of climate change uncertainties to water managers. In three workshops with water managers, the simulation game 'Sustainable Delta' was played to test the influence of the game on their understanding of climate change uncertainty using ex ante and ex post surveys. In each workshop an experimental- and control group were given different assignments to measure the influence of the game. The results show that although the differences between groups were not statistically significant, a change in their understanding of uncertainties was observed. The paper concludes that the learning effect of the game is inconclusive, but that the game does fosters a broader understanding of the concept climate change uncertainty. In doing so, simulation games is a promising approach to support the communication of climate change uncertainties meaningfully and support the process of adaptation to an uncertain future.

## 6.1 Introduction

Climate change projections are the principle source of knowledge for water managers to adapt their strategy to the expected intensification of the hydrological cycle due to climate change (Solomon, et al., 2007). However, scientific knowledge on climate change is incomplete and fraught with uncertainties. For example, it is uncertain how the earth system responds to changes in radiative forcings and how society responds to climate change by means of adaptation and mitigation strategies (Kunreuther et al., 2013). Even though it is well argued that uncertainty about climate change should not be a limit to adaptation (Maslin & Austin, 2012; Wilby & Dessai, 2010), water managers frequently report uncertainty as one of the most important barriers to adapt to climate change (Mozumder, Flugman, & Randhir, 2011). Several studies have argued that water managers require understanding of climate change uncertainties to make informed decisions, which includes information about the different types of uncertainty and some indication of the level of confidence in the projections of future changes (Tribbia & Moser, 2008; Wardekker, van der Sluijs, Janssen, Kloprogge, & Petersen, 2008). This information should be understandable and usable for decision makers (Tang & Dessai, 2012; Tribbia & Moser, 2008). Consequently, the communication of uncertainties from science and policy plays an essential role.

In general, communication on climate change takes place within the linear communication model where science 'speaks truth to power' (Hoppe, 1999): scientific research analyses the projected impacts and vulnerabilities, identifies possible response options, and informs politicians of these findings, often in codified forms (Weingart, et al., 2000). This linear model has been questioned in general (Hoppe, 2005; Huitema & Turnhout, 2009; Wesselink, Buchanan, Georgiadou, & Turnhout, 2013) and is for several reasons particularly troublesome in the context of communicating climate change uncertainties. First, climate change uncertainties have many different sources and it is not possible to quantify all the components (Alley et al., 2003; Dessai & Van der Sluis, 2007; Hall, 2007; Jones, 2000; Maslin & Austin, 2012). This makes the uncertainties complex and for scientists difficult to explain to decision makers. Second, climate science is a physical science and the term 'uncertainty' can be perceived by the decision makers as something that can be reduced. Scientists oftentimes reinforce this idea by expressing their confidence in the usefulness in climate projections and, more importantly, in their ability to continuously produce better information and reduce uncertainties (Lemos & Rood, 2010; Shukla et al., 2009). However, it is not likely that the large uncertainties will be reduced in the near future (Dessai, et al., 2009). Third, the issue of climate change is epistemologically and psychologically distant for many people and effects of climate change are not visible to everyone and some effects may take decades to occur (Carolan, 2004; Milfont, 2010).

Intermediaries or boundary objects might play an important role in clarifying scientific knowledge on climate change uncertainties by which the information becomes more understandable and useful for decision making (Clark, et al., 2011). In this context, boundary objects are instruments used to facilitate the interactions between science and practice and function as the operating space between different 'social worlds' in which actors come together and share interpretations without the need for consensus (Shackley & Wynne, 1996; Star & Griesemer, 1989). One specific type of intermediary that has recently been proposed for linking environmental science to policy are simulation games. Three noteworthy examples are: 'Keep Cool' a climate change board game developed to create a common language between students, scientists and public (Eisenack, 2012); 'WaterSim' a boundary object designed to bridge boundaries between scientific researchers and water policy stakeholders in central Arizona (White, et al., 2010); and 'Broken Cities' a strategy board game that requires participants to maximize rent while keeping carbon emissions under the limit (Juhola, Driscoll, Mendler de Suarez, & Suarez, 2013). Such interactive simulation games can be used to transfer or communicate complex scientific information into understandable and tailored information which is tacitly connected to the target group (Haug, et al., 2011). Despite the increasing attention to simulation games, no studies have used simulation games in communicating about climate change uncertainties.

The aim of this study is to explore the role of a simulation game in the communication of climate change uncertainties between science and water managers. More specifically, we analysed how a simulation game functions as intermediate in the understanding of the uncertainties on natural variability and human induced climate change of water managers in the Netherlands. We tested the influence of a simulation game with the 'Sustainable Delta', which is an interactive simulation game based on a hypothetical river stretch (Haasnoot et al. 2012; Valkering et al. 2012; Deltares).

## 6.2. Communicating climate change uncertainties: simulation games

Describing uncertainty on future climate change has proven to be a major challenge for the climate science community (Risbey & Kandlikar, 2007; Rob Swart, Bernstein, Ha-Duong, & Petersen, 2009). Making informed decisions on an inherently wicked problem, in which scientific uncertainty is an inevitable part in the construction of the problem, poses a considerable challenge to decision makers (Hoppe, Wesselink, & Cairns, 2013). Especially in the context of climate change, where decision makers depend heavily on trustworthy science to frame the problem and understand the costs and consequences of taking certain decisions (Demeritt, 2001; Webster, 2003). Scientific uncertainties can also undermine decision making, for example, when uncertainty is used as ammunition in decision making on controversial topics such as climate change (Pidgeon & Fischhoff, 2011). Better communication about climate change uncertainties is advocated by the climate change community for reasons of credibility and applicability of scientific findings, and is propagated by policy realm to make better informed and legitimate decisions on adaptation.

Communication is especially valuable when there are prevalent assumptions about climate change uncertainties that are erroneous from a scientific point of view. An example of this problem is the set of assumptions about the source of uncertainty in climate change projections. The uncertainties of climate change are characterized as large and complex by scientists, which can result in the misconception amongst water managers that the largest uncertainties for future water management emerge from human induced climate change rather than natural variability of the climate system. On the contrary; studies demonstrate that natural climate variability is one of the dominant uncertainties for short term changes in mean precipitation in Europe (Hawkins & Sutton, 2011) and for long term changes in extreme precipitation over the Rhine basin (Van Pelt, Beersma, Buishand, Van den Hurk, & Schellekens, 2013).

Human induced climate change involve new uncertainties that are difficult for decision makers to interpret and make sense of because they are ambiguous and unconnected to their existing frames of reference. To date, water managers have considerable experience in dealing with uncertainties associated to the natural variability of the climate system (Diefenderfer, Thom, & Hofseth, 2005), for example by dealing with unexpected floods or droughts. Even though it is scientifically known that the uncertainties of natural variability are large, the disconnection with the existing belief systems has influenced actors to believe that climate change uncertainties pose a significant barrier to adaptation (Adger et al., 2009). This can result in an overestimation of the uncertainties of human induced climate change compared to natural variability. Here, communication can be used to provide information in such a way that it deepens the understanding of the origin of uncertainties and support the conception that uncertainty should not be a limit to adaptation.

Communication about climate change uncertainties is understood as the process of bridging the boundaries between science and policy by characterising and translating scientific uncertainties. However, providing information about uncertainties (e.g. through reports, briefings, or presentations) in codified forms has limited effect. Unfortunately, limited alternative forms of climate change uncertainty communication exist of which hardly any examples of best practices (Patt, 2009).



Following the theoretical underpinnings of boundary work (Gieryn, 1983; Jasanoff, 1990), alternative ways to communicate uncertainties require to connect the different realms of science and policy by inhabiting the characteristic of both social worlds (Star & Griesemer, 1989). Within the science-policy nexus, there is ample room for dedicated institutions, agents, and objects that can help to connect the conceptual demarcations of science and policy. Boundary objects, the focus of this article, have several functions in the boundary work (Levina & Vaast, 2005); they are designed to connect to specific parts of science and policy and communicate particular information. They are hybrids that inhabit the intersection of different worlds. Boundary objects require a certain degree of robustness to maintain a common identity across sites and can be abstract or specific (Star & Griesemer, 1989); they form a portable and transportable concept that is applied to different settings (Star, 2010; White, et al., 2010). They can exist in many forms, such as an iconic extreme event (Lynch, Tryhorn, & Abramson, 2008) or imagery as polar bears (Slocum, 2004). Boundary objects can also be in a more interactive form, such as map tables and participatory scenarios (Ren, et al., 2011; Vervoort, et al., 2010). One specific form of boundary objects as interactive tool are simulation games. Simulation games have gained considerable interest over the past years (White, et al., 2010). They can help in the communication of climate change uncertainties between science and policy in four ways, namely:

- by combining and incorporating different sources of (scientific) knowledge about uncertainty and translating or simplifying the knowledge to make it accessible to the target group (Kriz, 2003).
- by connecting the abstract descriptions of uncertainty to the tacit knowledge of the target group by providing a real life experience (Haug, et al., 2011; Shackley & Deanwood, 2002).
- by directly showing the consequences of policy or individual decisions. A game exposes users to different conditions, settings, and renderings of the future. The game allows to present and calculate the effect of users current decisions (Juhola, et al., 2013).
- by using subject matter as a vehicle for learning about the influence of different forms of uncertainty. Simulation games stimulate thinking about the long term in an experimental setting (Haug, et al., 2011).

In sum, simulation games offer a way to span the boundaries of science and practice and allow to connect scientific information on uncertainties to prior believes by making the information tangible to decision makers.

## 6.3 Methodology

To explore whether the communication of climate change uncertainties can be improved by using a simulation game, five half-day workshops were organised between January - September 2013. This section describes the (3.1) selected participants, (3.2.) instruments for collecting data, (3.3.) the sustainable delta game (3.4) and the workshop and experimental design.

### 6.3.1 Participants: water managers and students

Two groups participated in this study to measure the effect of the game. The target group consisted of water managers using snowball sampling and existing network e.g. water boards, the province, or consulting companies that advice governmental institutes on river basin management in the Netherlands. Students were invited to play the game because they are not biased due to previous experiences in water management. The students were of different nationalities, although the Dutch nationality was dominant (70%). By comparing the results between students and water managers we can determine if the influence of the game is specific to the particular groups. Three workshops with water managers (A1, A2 and A3, N=20) and two workshops with students (B1 and B2, N=24) were organised.

### 6.3.2 Instruments for data collection

*Ex ante and ex post surveys:* The ex-ante survey aimed to collect information about: (a) the participants understanding of climate change scenarios, (b) their understanding of climate change uncertainty, (c) the role of uncertainties in climate change adaptation in water management, and (d) the participants backgrounds. Central to the survey were questions about their perception of the uncertainty of natural climate variability versus the uncertainty of human induced change. Similar questions were included in a shorter version of the survey which was employed after the experiment took place in order to test our hypothesis that the game influences the participants perception on natural variability and human induced climate change uncertainties. Supplementary information B1 and B2 provide the original surveys.

*Digital recording of discussions during the game:* To collect data about the influence of the game as communication instruments on climate uncertainties, the discussions among participants during the game were recorded and transcribed. Participants were informed beforehand about the recordings.

*Debriefing session:* After playing the simulation game, all participants were asked to share their experience and discuss collectively what they had learned from playing the game and how the game functioned in communicating uncertainties. Specifically, they were asked to reflect on their experiences on natural and human induced climate change. The debriefing session was digitally recorded.

*Follow-up email:* In September 2013, all water managers received an email asking them to reflect on the value of the simulation game in communicating climate change uncertainties.



### 6.3.3 Simulation game: Sustainable Delta

The simulation game 'Sustainable Delta' was used in the workshops (Valkering, van der Brugge, Offermans, Haasnoot, & Vreugdenhil, 2012). The game exists of a computational simulation model (Haasnoot, Middelkoop, Offermans, Beek, & Deursen, 2012) and a game board with cards and maps. Although originally developed for scientists to learn about the interactions between water management and societal and climatic changes, impression showed that the game was an effective way to learn about adaptive water management under uncertain change. The original game is described in detail in Supplementary information B3.


**Figure 6.1.** The Waas river strech

For this study, the traditional steps of the game were slightly altered to fit the purpose of the discussion of climate change uncertainties. The design of the game was pilot tested during two workshops with colleagues and two workshops with students, which resulted in a few additional adjustments to the design. The game consists of several rounds, in which the following sequential steps are taken:

1. *Discussion of group perspective and discussion on measures:* Each group decides what they find important and discusses the available measures. Measures are available to adapt to flooding and drought and to increase the nature area.
2. *Deciding future strategy:* The groups decide which measures they will take which fit their budget and the maximum number of measures they are allowed to choose.
3. *Implement measures:* The measures are implemented in the water system model. Results are calculated for a time period of 20-50 years.
4. *Water system impacts:* The main impacts on flooding, drought, nature development and economy are shown. They are visualized in graphs and tables and discussed with the participants.

### 6.3.4 Workshop and experimental design

Each workshop started with a survey. After all surveys were collected, the rules of the game and role of the participants were explained. Participants were introduced to the hypothetical 'Waas river stretch' case (see Figure 6.1) and were informed about the historical flood and drought events and possible response options in the case study area. After the introduction, the participants were randomly assigned in one of two groups with a minimum of 2 and a maximum of 8 participants. The two groups went to separate rooms to minimize influence of the group.

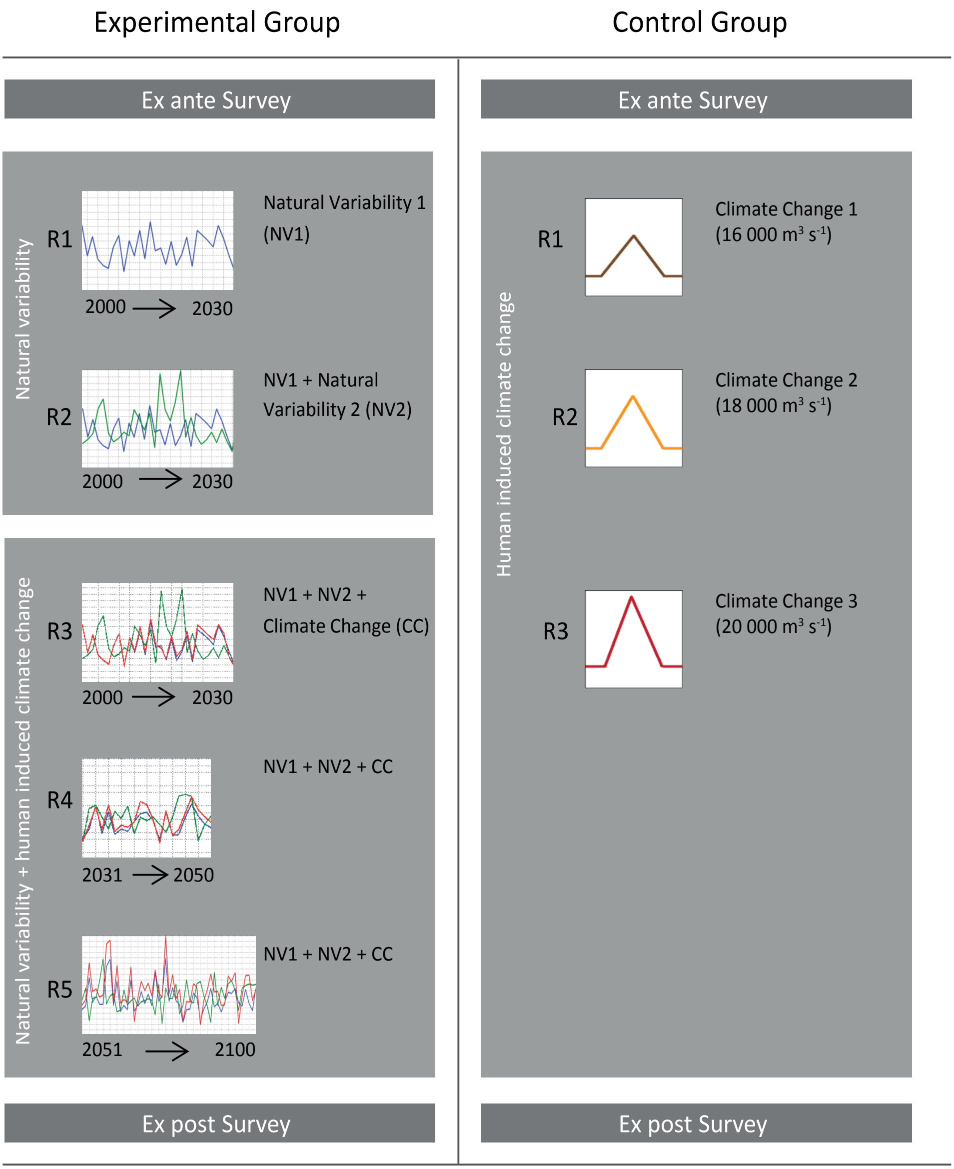


**Figure 6.2.** Synthesis of experimental setup. The workshop started with a survey. In different rounds (R) the experimental and control group were provided with new information.

*Experimental group:* The experimental group started with historic and current trends of natural variability (familiar uncertainties) in the form of transient scenarios and were confronted with human induced climate change information later in the game. In round 1, participants were confronted with runs of natural variability for the time period 2000-2030. In round 2, a second run of natural variability was added to demonstrate the difference between natural variability runs. In the third round, the participants were confronted with a human induced climate change scenario. In rounds 4 and 5, the time period was extended to 2050 and 2100, respectively.

*Control group:* The control group played the game with human induced climate change (unfamiliar uncertainties). They were asked to design a robust adaptation strategy for different design discharges. The design discharge is the peak discharge corresponding to a return level. The base line design discharge of the hypothetical river basin was set to be approximately 10,000 $m^3s^{-1}$. In the first round the participants were asked to design a robust adaptation strategy for a design discharge of 16,000 $m^3s^{-1}$. In the second and third round, the design discharges increased to 18,000 $m^3s^{-1}$ and 20,000 $m^3s^{-1}$, respectively. After three rounds, the experiment was finished and the participants of the control group filled out the second part of the survey.

We hypothesised that by demonstrating the uncertainties of natural variability and gradually introducing human induced climate change, the experimental group would learn about the influence of natural variability to the overall climate uncertainty. Directly after the game and before the debriefing, the participants of the two groups are asked to complete the ex post survey. We expect that, if the game functions as learning instrument, water managers (or students, which played the game in separate workshops) of the experimental group will perceive the role of natural climate variability to be larger after playing the game.

## 6.4 Results

### 6.4.1 Results of the pre-game survey among participants

The majority of water managers (70%) and over a third (40%) of the students believed that the uncertainty about changes in a future climate will decrease through scientific research, see Figure 6.3a. Additionally, the majority of the water managers (68%) prefers climate change adaptation measures that are robust against the most likely climate change scenario, a scenario that can impossibly be developed due to the nature and number of uncertainties (Dessai & Van der Sluis, 2007), see Figure 6.3b. This confirms the assumption in our introduction that water managers as well as the students, believe that climate change can be projected with high levels of confidence. There is a gap between what scientists can deliver (or think they might be able to deliver in the future) and the expectation of the users of scientific knowledge, in this case the water managers.

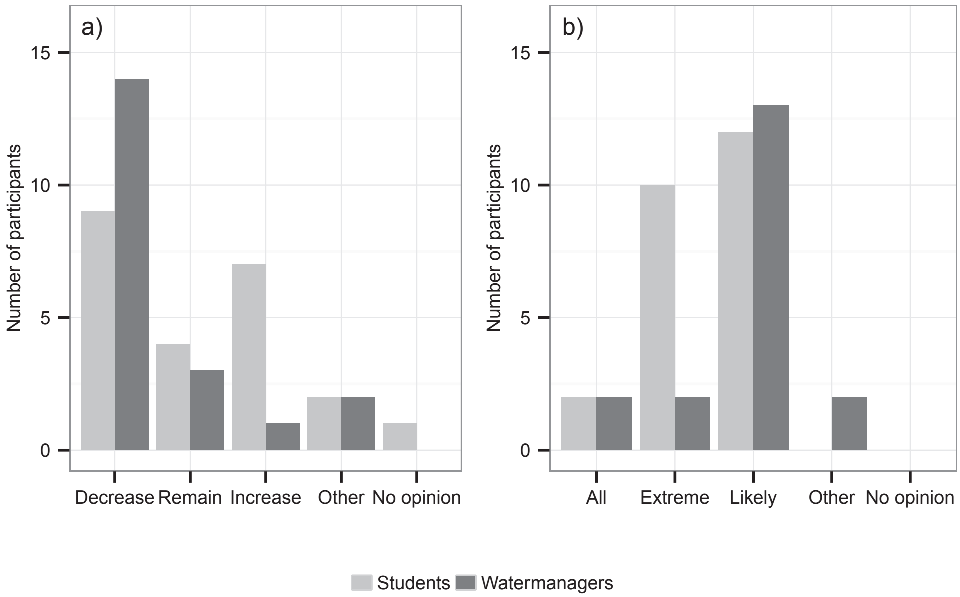


**Figure 6.3.** a) Response of participants to this question: *"I expect that, through scientific research, the uncertainty about changes in a future climate will:..*" b) Response of participants to this question: *"As a water manager I would choose climate adaptation measures that are robust against ... climate scenario(s).*"

To understand the complexities attributed to the concept, the workshop participants were asked to describe of climate change uncertainty (open question). The data was analysed using open coding methods. The synonyms, sources and examples of uncertainties mentioned by the participants are presented in Table 6.1. The findings suggest that there are different interpretations about the concept uncertainty. Notable was that the term climate change was also linked to climate variables such as temperature, precipitation and sea level rise. The variety of synonyms, the different sources and examples of uncertainty demonstrates that the term 'climate change uncertainty' is complex and multi-interpretable.

**Table 6.1.** Clusters of words and excerpts from the ex-ante survey when asked "*Could you describe your understanding of the concept climate change uncertainty*" (Q5).

| | Water managers (n=20) | Students (n=24) |
|---|---|---|
| Form of expression of uncertainty | degree of unpredictability; unpredictability; degree to which you are (not) able to predict; no clarity about the lower bound; outside the regular or known climate pattern; degree/extent; could be just another movement or direction; unclear which direction it moves; always something else. | may not be exact all time; not be able to predict in advance; unclear (3x); don't know everything; forgotten; difficult to determine which are correct; no one knows exactly what is going to happen; are not known yet; not known how exactly; estimate; range of possible values; spread; everything within; maximum or minimum. |
| Source of uncertainty | climate scenario; emission scenarios; expected development; that what is expected; G or W+ relative to the expected trend; climate models; with respect to the exact development; long term; future climate; future; the rate of climate change; climate (2x); climate change (2x); change; effect of climate change; change of climate; how climate will change; operation of the system; temperature; precipitation; extreme events; the actual response of climate to change or human influence, human influence.different information flows. | predictions (6x); climate change (5x); scenario(2x); future (2x) forecast, climate (2x); several scenarios; several projections; predicting climate change; risks; future climate change; with any time frame; climate on the long term; how fast; the next few years; the climate machine; climate is changing; phenomenon of climate change; climate has a lot of fluctuations; influence of climate; climate will change; climate trends; climate on each location; feedbacks; different variables; not all factors have been mapped out; temperature; precipitation; wind; change of weather and temperature; factors; causal links; development of human kind in the next 100 years; influence of human kind; different studies with different outcomes. |
| Example in which uncertainty is visible | warming vs. cooling; the environment; the effects; the consequences. | adaptive strategies with respect to the environment (spatial planning); choices/ measures; sea level rise; natural disasters; more frequent and extreme precipitation; drought; flood; earthquake; people; infrastructures (natural or not); impacts/ risks; extreme event; effect (directly and indirectly); impact in a massive way; the expected effects. |

### 6.4.2 Contribution of the simulation game to the communication of uncertainties

The water managers indicated that playing the simulation game had an added value for them. Several reasons were mentioned during the debriefing. First, the game was considered to have a psychological impact; the participants experienced what happened when certain decisions were taken and what the role of uncertainties was, as stated by one participant: "*It is psychological strong, the effects of uncertainties and accidental events are experienced by us and also which impacts they have on the system*" (A2, experimental group). It made the knowledge more tangible. Second, the game activated the participants to take up knowledge about climate uncertainty. The participants noted that they felt a high attention level during the game, which continued into the debriefing:

"*As a listener I was activated, and I experienced first-hand that flooding also happens without climate change, this really woke me up, especially because we just zealously developed a strategy to prevent that*"(A3, experimental group). Third, by playing the game participants learned about the uncertainties and the role of natural climate variability, as stated by one participant: "*For me it was an eye-opener to experience the relation between the natural fluctuations and the influence of human induced climate change*" (A3, experimental group).

The water managers found the game interesting as it allowed them to consider the effects of selected measures immediately. Moreover, the game does not only address the effect of the selected measures, but is also helpful to acknowledge and better understand various climate challenges and explore responses. The game lets the participants experience what may happen if they do not take action. A number of participants mentioned that the game would also be beneficial for communication processes. As noted by one water manager: "*The game facilitates in sharing conclusions with each other. It helps to get new people to the same knowledge level. The visual experience is really important. You can write many reports, but in the game you learn how to make choices*" (A2, experimental group). There were also some people who mentioned the importance of planning for the long term. The game made them realize that this is important and it helps you prepare for the future. Students agreed about the value of the game in understanding the climate change uncertainties. For example, the students often mentioned that the game learned them that taking decisions under uncertainty, but also taking into account factors other than climate change, was much more difficult than they had expected.

### 6.4.3 The effects of the game on the perception of natural climate variability

*Ex-ante and ex-post survey results:* The results of Figure 6.4a show a change in the perception of uncertainty of natural climate variability for the water managers in the experimental group. The water managers in the experimental group perceive the uncertainty of natural climate variability compared to the uncertainty of human induced climate change to be larger after the game. The control group shows the opposite, after playing the game they perceive the uncertainty they would attribute to human induced change larger. Of the 10 water managers in the experimental group, five respondents changed their answers in the ex post towards a more important role of natural variability. Two participants changed their answers as being lower, three participants remained the same. For the 10 water managers in the control group only three participants changed their scores, with one participant scoring higher and two lower. In the ex-post survey, participants could indicate that if they change why they changed their answer after playing the game (open question, Q6). As one participant noted "*The erraticism of climate change is more important than I thought*". The results of this test could not be confirmed with statistical significant difference between the experimental and control groups.

*Debriefing results:* Directly after the game, the water managers were asked to reflect whether playing the simulation game provided new insights about the role natural variability compared to human induced climate change. A few water managers indicated that, before the game, they already considered the uncertainty of natural variability to be quite high. Several water managers indicated that their perception did change after playing the game. As one water manager noted: " *I already thought that natural variability was important, but I did not expect the realisations to be like that. The variability was larger than I expected*" (A2, experimental group). Other managers said that their perception did not change per se, but that the game did stimulate thinking about the topic.

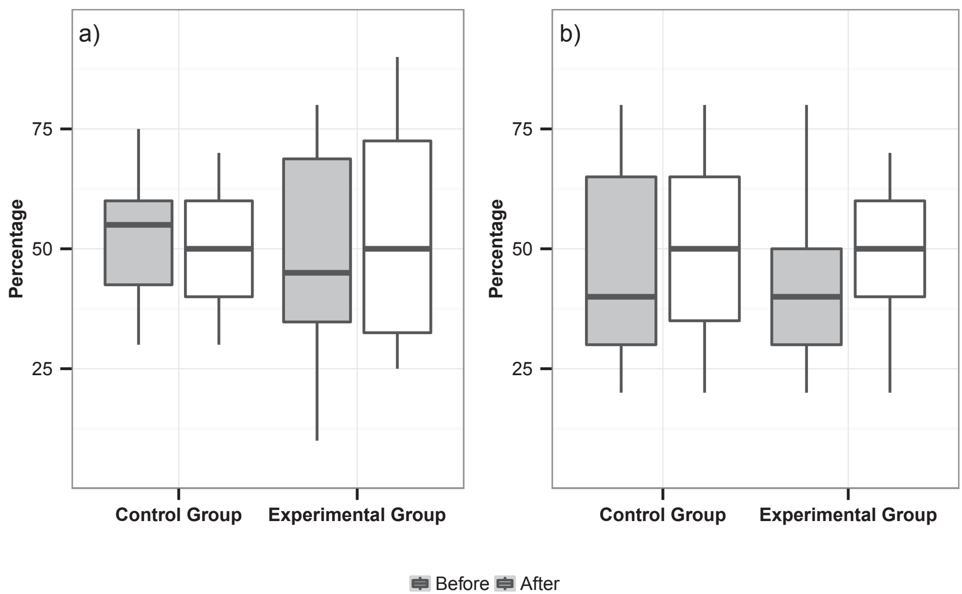


**Figure 6.4.** Distribution of answers to the question: *"If you were asked to divide uncertainty about the future climate in two component, which percentage of uncertainty would you attribute to natural climate changes and which percentage would you attribute to human induced changes?"* The figure shows results for the percentages attributed to natural climate change, before (Q16) and after the simulation game was played (Q6). a) Shows the results for the water managers and b) shows the results for the students.

## 6.5 Discussion and conclusions: communicating climate change uncertainties by using simulation games

The aim of this study was to explore the role of simulation games in communicating climate change uncertainties. We were particularly interested in the learning effect of water managers about the relative role of uncertainty due to natural variability compared to human induced change. To this end, the simulation game 'Sustainable Delta' was used in workshops with water managers and students. Several observations can be made.

Our findings suggest that the simulation game can have a positive effect on learning. On the one hand, our hypothesis that the experimental group would show a change in perception on the distribution of natural variability versus human induced climate change after playing the game could not be confirmed with statistical significance. This could be caused by the small sample of participants in the simulation game. There are, however, high costs associated with setting up and implementing simulation game experiments. On the other hand, fifty per cent of all water managers in the control group changed their perception and attributed a greater influence of natural variability after playing the game. To conclusively state to what extent the simulation game is a useful instrument would require a larger number of observations. Additionally, future research could place more emphasis on the learning effect by including learning specific indicators, as for example suggested by Haug et al. (2011). However, given the need to stimulate learning about climate change uncertainty, our findings legitimize the use of the simulation game.

Our findings suggest that simulation games can be an useful instrument in the communication of climate change uncertainties for several reasons. First, the results show that the game is helpful in explaining the uncertainties and the different types of uncertainty. The participants indicated that they were better informed about climate change uncertainties and the relative role of natural variability compared to human induced change, this was also reported by other studies, see for example Lonsdale (2008). Second, the game fosters a broader understanding of the concept of climate projections and the unpredictability of some processes. In the debriefing, the participants indicated that some projections were unexpected and that the game learned them about dealing with unpredictability of future climate changes. Third, the game reduces the psychological distance of climate change, as the participants experience the effects of adaptation measures that can be taken in a real life simulation. It connects to the causal beliefs of the participants. Here, visualisation played an important role, something which is also found in several other studies (Burch, Sheppard, Shaw, & Flanders, 2010; Sheppard, 2005; Wardekker, et al., 2008). Fourth, the simulation game created a level playing field that allowed participants to experience different realities and demonstrated how changing the initial conditions influenced their decisions. The debriefing allowed them to discuss their experiences creating an collectively discussing the role of natural variability and human induced climate change.

Thus far, the role of simulation games as specific instruments for communicating uncertainties has remained underexplored. Games are increasingly used as way of communication on climate change. Reckien and Eisenack (2013) identified over fifty different climate change games that aim to increase the awareness and understanding of climate change of the general public. Simulation games have been used to co-create knowledge about where to make certain measures and to inform decision makers about the climate change risks, costs of certain measures or effect of taking certain measures. Despite some limitations, the simulation game used in this paper offers a promising and much needed instrument in the communication of climate change uncertainties to policy makers (Patt, 2009). Using simulation games creates a novel platform for knowledge exchange and enhance the understanding of climate change and the different types of uncertainties associated.

Simulation games in general and the "Sustainable Delta" game in particular can be conceptualized as a boundary object in science-practice communication. The typical characteristics of the game, make it a portable and transportable concept, that can be applied to different settings (Star, 2010; White, et al., 2010). Earlier studies that have used the game in different settings demonstrate its versatility (Haasnoot, et al., 2012; Valkering, et al., 2012). Star and Griesemeier (1989) argue that an important aspect of a boundary object is its ability to intersect different social worlds. The 'Sustainable Delta' game allowed participants from different water management agencies to come together and discuss future water management. Although scientists were no active part of the game session, they interacted with the water managers through the game. Also, the game has a meaning in both the water managers and scientists world and keeps its identity during the game sessions, while at the same time the game is flexible enough to take into account the demands of the developers and users and allow for modification to deal with changing circumstances (Bowker & Star, 2000; Turnhout, 2009). So the simulation game, within the boundary arrangement of the workshop, functioned as a boundary object.

A broader observation from this study is that participants recognized that uncertainty is a complex concept with many synonyms, sources and examples, making it especially complex to communicate about, see Table 6.1. As a concept, uncertainty is sensitive to many different interpretations as it is used in many different settings and contexts. Within the scientific community, uncertainty is an important if not necessary attribution to any good measurement or finding. However, there are on-going debates about how to describe (i.e. qualitatively or quantitatively) the uncertainties of climate change in a coherent and meaningful way (Patt & Dessai, 2005; Swart, et al., 2009). Some scientists rather avoid communicating probabilities especially when they suspect that the decision makers do not have the skills to understand them properly (Hall et al., 2012). It is possible that this stems from their concern that scientific uncertainties are underplayed, overplayed, misused or ignored for the purpose of decision making, and thereby undermining the legitimacy and credibility of climate science. Outside the scientific realm, the notion of uncertainty has a negative connotation. Scientific uncertainty is often placed on equal footing with flawed science or is interpreted as unsettled science. Uncertainty is where climate science can be the most vulnerable (Nisbet & Scheufele, 2009). Importantly, the concept of uncertainty serves different roles in the science and policy realms; where uncertainty drives science forward in search for better explanations, it is the same uncertainty that leads policy makers to indecisions. Communicating uncertainty is thus a delicate task that needs to take into account the opposing discourses about the concept. The simulation game as boundary object fulfils such a role as it allows for communicating about uncertainty without explicitly referring to the concept. The game offers a neutral platform for non-persuasive communication by trusting the scientific evidence to speak for itself by letting decision makers experience the uncertainty in a real-life setting (Fischhoff, 2007).

During the debriefing, several water managers indicated that uncertainties about climate change are not always important to them, because, there are several other uncertainties which they have to take into account. This argument was also made by Koppenjan and Klijn (2004) who suggest that uncertainty about the information (substantive uncertainty) is one of three sources of uncertainty in decision making. There are also uncertainties about strategic behaviour of actors in the decision making process (strategic uncertainty), and uncertainties about the differences in institutional backgrounds (institutional uncertainty). For example, decision makers have to take into account the costs of a specific measure and how the public will respond to certain decisions and change their behaviour accordingly. In this study, we have used the simulation game to communicate about substantive uncertainty, but the game could also be used (with slight modifications) to simulate the influence of other types of uncertainty on the decision making process.



Overall, there is preliminary evidence which suggest that the simulation game, as novel boundary object, can be used to support the communication of climate change uncertainties meaningfully and, by doing so, support the process of adaptation to climate change.

**Acknowledgements** The authors would like to thank the participants of the workshops for their enthusiastic contribution. This research was carried out in the Dutch National Research Program 'Knowledge for Climate' Theme 6. Any omissions remain our own responsibility.

# Chapter 7

## Synthesis

## 7.1 Overview of presented research

The principal aim of this thesis was to analyse the climate change uncertainties that are important to take into account for long term water management and to explore the communication of these uncertainties.

The Rhine basin was used as case study area for this thesis. In chapter 2, an overview was presented which highlighted several important challenges for future flood risk management in the Rhine basin. In chapter 3 and 4 the uncertainties for long term changes in mean and extreme precipitation over the Rhine basin were studied, using a large ensemble of global and regional climate models. The HBV model was used to study the effects of these changes on discharge in the Rhine basin. Chapter 5 presented a new methodology to study the probability of changes in flood risk and the associated damage using large ensembles of climate models. The knowledge about the uncertainty of changes in flood risk, generated in chapter 3 to 5, can support adaptation decision making, therefore, in chapter 6 the effect of a simulation game on the communication of climate change uncertainties to water managers was analysed.

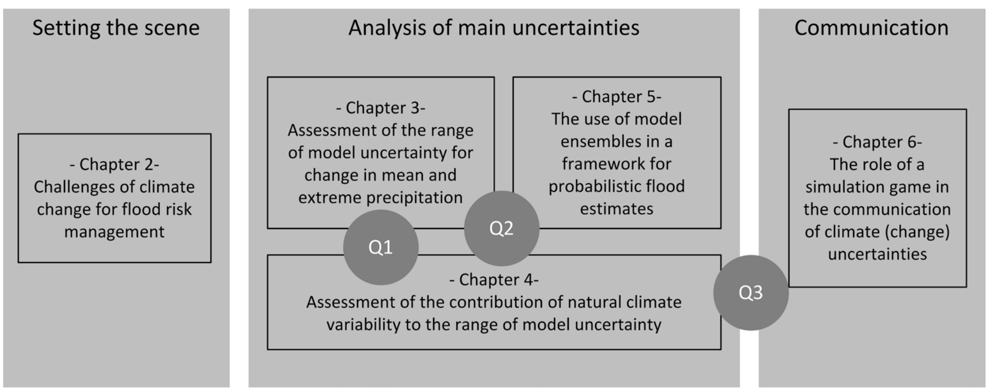


**Figure 7.1.** Overview of chapters and research questions.

This final chapter discusses the key findings of the thesis. The research questions, as presented in the introduction, are discussed in a broader context in section 7.2. In section 7.3 the main scientific contribution is discussed. Suggestions for future research are given in section 7.4 and recommendations for water management are presented in section 7.5. This chapter concludes with a short epilogue.

## 7.2 Discussion of research findings

*Q1: Which type of uncertainty is dominant for explaining long term changes in average and extreme precipitation and discharge in the Rhine basin?*

*Key finding 1:* Epistemic uncertainty is dominant for changes in mean precipitation and discharge over the Rhine basin.

The dominant type of uncertainty depends on the climate variable of interest. Flood events in the Rhine basin downstream of Maxau often occur in the winter or early spring (Beersma, Kwadijk, & Lammersen, 2008) and are most influenced by changes in multiday precipitation sums (Disse & Engel, 2001; Ulbrich & Fink, 1995). Precipitation response over the Rhine basin is mainly determined by large-scale circulation changes, which are captured by the (driving) global climate models (GCMs) (Lehtonen, Ruosteenoja, & Jylhä, 2013). Other studies have also shown that for flood risk management the global climate response is the largest source of uncertainty (Chen, et al., 2011; Dobler, et al., 2012; Kay, et al., 2009; Liebert, et al., 2012; Prudhomme & Davies, 2009; Velázquez, et al., 2013). Therefore, in this thesis we studied the partitioning of epistemic and stochastic uncertainty in a large ensemble of GCMs.

An ensemble of 12 GCMs was used to get an estimate of the range of uncertainty. The changes in 5-day precipitation sums, averaged over the basin and the winter half-year (October-March), were analysed for the periods between 1961-1995 and 2081-2100. The output of the climate models showed disagreement over the sign of change. Some models showed a positive change ranging to +18%, whereas others showed a negative change, ranging to -11%. Epistemic and stochastic (i.e. internal variability) uncertainty are both represented in this uncertainty range of climate model output. Several studies have demonstrated that stochastic uncertainty is a significantly more important factor for changes in precipitation than for changes in temperature (Hawkins & Sutton, 2011; Murphy, et al., 2004; Jouni Räisänen, 2001). The relative contribution of the different sources of uncertainty depends, however, on the time period and geographical area of interest. An analysis of 14 CMIP3 models by Hawkins and Sutton (2011) showed that for changes in mean precipitation over Europe, stochastic uncertainty is dominant for short lead times, while epistemic uncertainty starts to dominate after about 50 years. Scenario uncertainty plays only a very small role at every time scale. Therefore, we did not include scenario uncertainty in our analysis in the studies presented in chapter 3 and 4. The findings of this thesis show that for changes in mean winter half-year precipitation over the Rhine basin at the end of 21$^{st}$ century, the contribution of stochastic uncertainty is approximately 30%. This is comparable to the results of Hawkins and Sutton (2011) for changes in winter precipitation over Europe.

It is complicated to assess which adaptation strategies should be implemented due to the conflicting sign of the GCMs over the change in mean winter precipitation. When the results of the climate models are averaged, an increase of 8% is projected. Combining this with a temperature increase, which is likely to result in earlier snow melt (Barnett, Adam, & Lettenmaier, 2005), the mean discharge in the Rhine basin is most likely to increase in the winter period, which is in line with other studies (Hurkmans, et al., 2010; Lenderink, Buishand, et al., 2007; Pfister, Kwadijk, Musy, Bronstert, & Hoffmann, 2004; Te Linde, et al., 2010). The dominance of epistemic uncertainty for changes in mean precipitation over the Rhine basin shows that for the development of adaptation strategies it is important to assess the output of a (large) ensemble of climate models.

*Key finding 2:* Stochastic uncertainty is dominant for changes in extreme precipitation and discharge.

High discharge events in the (lower) Rhine basin mainly occur in (late) winter (Pfister, et al., 2004; Waterdienst, 2012) and, therefore, we assessed changes in extreme winter half-year precipitation.

Changes in extreme precipitation over a range of GCMs outputs were assessed between 1961-1995 and 2081-2100. An exploration of the sensitivity of extreme quantiles showed that the use of $P_{90}$ and $E_{90}$ (part of precipitation above the 90% quantile, $E_{90}= P- P_{90}$) was preferred over higher quantiles such as $P_{95}$ (see also Supplementary information A1). The modelling uncertainty could be mainly attributed to the uncertainty of changes in the mean of the excesses $\overline{E}_{90}$, as these changes are (much) stronger than changes in $P_{90}$ The change in $P_{90}$ and $\overline{E}_{90}$, as simulated by the ensemble of GCMs, showed a robust positive signal. This is in coherence with other studies regarding changes in precipitation extremes in Europe (Beniston, et al., 2007; Buonomo, et al., 2007; Frei, et al., 2006). Compared to changes in mean precipitation, however, there is a large intermodal difference in the magnitude of change, which was also shown in other studies (e.g. Hegerl, et al., 2004). This larger intermodal difference was supported by the larger increase in standard deviation of 5-day precipitation sums than the change in the mean (see also Table 3.3 in chapter 3).

In chapter 4, a first analysis of the contribution of stochastic uncertainty to the intermodal differences for changes in extreme precipitation over the Rhine basin was presented. Stochastic uncertainty explains about 40% of the intermodal differences for $P_{90}$, which means that epistemic uncertainty is still dominant for this variable. For $\overline{E}_{90}$, it was suggested that stochastic uncertainty explains 100% of the intermodal differences. Thus, based on these findings, stochastic uncertainty is the dominant type of uncertainty for changes in precipitation above the 90% quantile at the end of this century. The discrimination between internal variability and model uncertainty was, however, quite inaccurate, which could be mainly attributed to the limited ensemble size.

The contribution of natural climate variability was also assessed for long return periods up to 1,000 years. This assessment was done for both precipitation and discharge, but it was not possible to take bootstrap samples of these long time series. Therefore, we compared changes of 17 members of a single GCM (ESSENCE) with changes in the GCM ensemble. The range of uncertainty for changes in the ESSENCE ensemble was similar to the range in the GCM ensemble. This was in line with the large contribution of stochastic uncertainty to changes in extreme precipitation, assuming that the range projected by ESSENCE is representative also for variability of the other GCMs.

The dominant types of uncertainty identified for long term changes in mean and extreme precipitation, namely epistemic and stochastic uncertainty, are potentially reducible through progress in climate science. Human reflexive uncertainty, which is reflected in the scenarios, is less likely to be reduced, because it is difficult (or even impossible) to quantify this type of uncertainty. This type of uncertainty, however, does not play a significant role in the total uncertainty of changes in extreme precipitation. Therefore, the observation of Lorenz et al. (2013) that there is a bias across countries towards the communication of uncertainties that are perceived to be more quantifiable at the cost of communicating more qualitative uncertainties (such as future socio-economic conditions), is not a concern for communication about the uncertainties of (long term) future flood risk in the Rhine basin. Nevertheless, the potential for epistemic and stochastic uncertainty to be reduced should not be used as an argument for inaction. Reduction in epistemic uncertainty would only give substantially more confidence in projections of change in precipitation at longer time scales (mid-late 21$^{st}$ century) because of considerable internal variability relative to the climate change signal for the next decades (Hawkins & Sutton, 2011). Although, some evidence suggests that for extreme precipitation there might be a bit more confidence in the signal to noise ratio (Hegerl, et al., 2004), a view supported by Fowler and Wilby (2010) who found that significant changes in multiday extreme winter precipitation could emerge in some parts of the United Kingdom within a decade.



Although knowledge about the role of natural climate variability in the total uncertainty of climate change could be of value to adaptation planning, it has hardly penetrated the scientific and policy debates on climate change adaptation. Yet, if we want to adapt to climate change through proactive and planned measures we need additional efforts that are not only intentional, but also substantive in addressing the human induced part of climate change (Dupuis & Biesbroek, 2013). Assessments as done in this thesis, that try to disentangle the contribution of natural climate variability from other sources of uncertainty are needed to support this type of adaptation planning. In doing so, it makes an important contribution to thinking about climate change adaptation.

*To summarize the findings of research question 1*: the uncertainties that are important for changes at the end of the 21st century over the Rhine basin are mainly determined by the global climate response. Within this response, epistemic uncertainty is the dominant type for mean precipitation, whereas this shifts to stochastic uncertainty in the case of extreme precipitation above the 90% quantile. These findings demonstrate the importance of both categories of uncertainty for long term climate change over the Rhine basin. This knowledge can support scientists and decision makers to explore future pathways and test current or planned systems to changing conditions. Moreover, it can support the development and evaluation of intentional and substantive adaptation strategies.

*Q2: What is the impact of climate change uncertainties on changes in flood risk and the associated damage in the Rhine basin?*

*Key finding 3:* Large climate model ensembles cover a large part of the uncertainty space and are therefore essential for analysis of flood risk.

Most flood defence measures are designed to last for long periods of time. Their development and management requires insight and anticipation on future changes in flood risk. It is difficult to translate long term changes into specific strategies, because they are inherently uncertain. To support this type of decision making it is important to gain knowledge about the main uncertainties that determine the uncertainty space.

Chapter 3 was based on the results of a 6-member RCM ensemble from the Rheinblick2050 project, forced by four GCMs. Although RCMs have a much more detailed topography and are able to solve smaller scale physical processes, the largest uncertainty for projections of future change in precipitation extremes is linked to the driving lateral boundary conditions given by the GCM (Fowler & Ekström, 2009; Leander, et al., 2008). Results from a study of Kendon et al. (2010) state that given limited computer resources, ensembles for analysis of precipitation, which is important for flood risk, should be designed prioritizing the sampling of GCM uncertainty, using a reduced set of RCMs. Therefore, the 6-member RCM ensemble was extended with eight GCMs, post-processed using the advanced delta change approach. Surprisingly the total model spread of the GCM ensemble was only slightly larger than the spread of the RCM ensemble. The selection of the RCMs in the RheinBlick2050 project was apparently not biased with respect to changes in extreme precipitation, imposed by a small ensemble of driving GCMs. A prior selection of outlier climate models which represent upper and lower values could give a large model spread but this knowledge is not always available before selection. In addition, the models that gave the highest values for changes in the mean do not necessarily gave the highest value for changes in extremes. Therefore, a subsample of the RCMs or GCMs could lead to an underestimation of the uncertainty range.

For the studies in chapter 3, 4 and 5 we used multi-model ensembles without applying weighting, even though some models seem to perform better than others. The different GCMs varied in construction and contain different parameterizations of climate processes and different methods for numerical integration. Research has shown that no model performs better than all others in all aspects (Gleckler, Taylor, & Doutriaux, 2008). As such, we considered the ensemble as sampling at least some of the uncertainties in a climate model. Furthermore, the ability to simulate the current climate well might not be the best indicator for the ability to simulate the future climate. Strictly spoken, the models cannot be calibrated or evaluated, as the projections refer to a state that has not occurred yet.

There are four limitations to the use of multi-model ensembles, which have lead Stainforth et al. (2007) to recommend that a climate model ensemble should be presented as a 'lower bound of maximum uncertainty'. First, although each model has its own combination of parameters to approximate the real world, the models are not all independent (Jun, Knutti, & Nychka, 2008). Some models belong to the same model 'family' and share certain parameterizations. Second, the model ensemble is not sampled randomly or systematically. Most groups or institutes provided their 'best' model to the CMIP3 archive (Knutti et al., 2010). Third, often a sample of GCMs is chosen from the available models, based on opportunity and time and resources available. This was also the case in this study in which we used 12 GCMs. The different samples made it difficult to compare our study to other studies. Fourth, the outputs of these assessments cannot be treated as predictors of the future because, the value is always dependent on the ability of climate models to simulate the 'real' climate. A current weakness of the global climate models is that they have great difficulty in reproducing the observed trend of precipitation over Europe (Van Haren, Van Oldenborgh, Lenderink, Collins, & Hazeleger, 2013). A correct representation is one of the important (but not only) conditions for confidence in the ability of climate models to project future changes. Thereby, conveying adequately how much or little confidence can be placed in the ensembles poses another communication challenge (Stephens, Edwards, & Demeritt, 2012). The four limitations are important to consider when the results of an ensemble study are assessed. The studies do not sample the full range of uncertainty and the outputs are dependent on the ability of the models to simulate the climate. When the ensembles are used for impact assessments, than the actual 'best case' or 'worst case' outcomes might be missed (Knutti, et al., 2010).



Extracting information that can support decision making from an ensemble of climate models, as presented in this thesis, is difficult. Even if the ensemble seem sufficiently large, it does not capture the full range of plausible models, which makes it likely that the range is too narrow. The deep uncertainties of the model ensembles result in a need for communication about how much or little confidence can be placed in the ensemble. The ensembles do give us, however, the opportunity to assess plausible futures. Compared to using only one or two estimates, they give us a much broader view of possible changes and thus a better chance to prepare for these changes.

*Key finding 4:* The probabilistic framework proves to be very useful for the assessment of potential damages, but the results should be interpreted with caution in order to avoid misinterpretation.

In chapter 5, a framework was developed for estimating the probability distribution of flood risk. The risk assessment was the first demonstration of such a methodology. A simple inundation model was coupled to a damage model to make a probability distribution of flood risk under future climate scenario conditions. The resulting framework allowed to assess the probability that flood risk will increase by a given factor. Assuming the A1B emission scenario, the probability that the future flood risk exceeds the current flood risk is more than 90% for two case studies in the German part of the Rhine basin. The main value of this method is that the framework is not too complex, it does not take a lot of time or resources (e.g. through computer modelling). In a few steps the potential changes in flood risk and the associated damage can be assessed for a given area.

A few improvements could be made to the probabilistic framework as presented in chapter 5. First, we used an ensemble of 12 GCMs and 6 RCMs. Although this is a large ensemble an even larger ensemble is preferred to describe the probability density function of risk with a theoretical distribution. Second, one member per GCM was used in the presented study. This means that for this study no ensembles with perturbed initial conditions were used and, therefore, we were not able to assess the role of natural climate variability. Third, the time series that were used in the study were rather short for the assessment of extreme precipitation and discharge. We did use 3,000 year resampled time series to assess long return periods, but the changes were still derived from only 35 and 20 years of data. This study would be improved when longer time series would be used, as this would reduce the sampling variability for extremes, especially. The use of larger ensembles with multiple runs is also advocated by Kendon et al (2008) and Kew et al (2011) to improve the detection of changes in extreme precipitation.

Probabilistic assessments of the impacts of changes in flood risk are useful but there are few pitfalls. First, it is possible that too much trust is put in the estimates. It should be well communicated that the probabilities are based on model results and not the real world. This is, of course also true for non-probabilistic scenarios, but assigning a certain chance to an event may lead to overconfidence (Marx & Weber, 2012). The probabilities inform about the uncertainty within an ensemble of climate models. Second, the explanation of probabilities to decision makers is quite difficult. This was also exemplified by the problems of the Fourth IPCC assessment report with the terms describing probabilities. Often the probabilities are not interpreted correctly by users (Budescu, Por, & Broomell, 2012; Patt & Dessai, 2005). Third, when applying probabilities, users have a preference for the central estimate and interpreting this as the most likely estimate (Gawith, et al., 2009). User guidance is one of the main conditions for users to discern the most appropriate scenario as shown by Wilby and Dessai (2010) in a response to the experience with the UK Climate Projections (UKCP09), which was the first large scale project that quantified the uncertainty of each climate projection by assigning a probability. Fourth, the use of precise probabilities can be confusing; this was shown by an example in the study of Kunreuther et al. (2013), in which the probability of equilibrium climate sensitivity exceeding 4.5 °C ranges from less than 2% to over 50% in different studies. These four pitfalls illustrate the importance of a careful consideration of probabilities. If probabilities are not interpreted correctly they may lose their value and can hinder instead of aid robust adaptation.

*Key finding 5:* In addition to dynamical downscaling, the advanced delta change approach is a valuable tool for processing large amounts of climate model data because, it is relatively simple and therefore not resource and time intensive.

The low spatial resolution of the GCM output does not match the data requirement of the HBV model. Therefore, it is necessary to perform some post-processing upon the output of the GCM. In chapter 3, dynamical downscaling by bias-corrected RCMs is compared with the use of the advanced delta change approach. RCMs are developed to simulate finer-scale physical processes consistent with the large-scale weather evolution prescribed from a GCM. The main problem of RCMs are the computational costs. Large ensembles of RCMs are, therefore, often only driven by a small number of GCMs because, it is not feasible to complete a full matrix of every GCM-RCM combination. The delta change approach can be used as a simple and less resource and time intensive method to post-process GCM output. Graham et al (2007) stated, however, that the use of the delta change approach offers a robust method to compare average outcomes of different climate models, but is less suitable for the assessment of hydrological extremes.

In chapter 3 the sensitivity of the advanced delta change approach, based on work of Shabalova et al. (2003) and applied by Leander and Buishand (2007) for the Meuse basin, was assessed and the method is improved accordingly. The method was used to post-process the output of a large ensemble of GCMs and the results were compared to the bias corrected RCM output for changes in mean precipitation and changes in extreme precipitation. This comparison showed that the advanced delta change approach is a valid method for the analysis of changes over the Rhine basin for extremes as well.



The study of Kew et al. (2011) showed that even a simple delta-change technique could be adequate for modelling basin-scale changes in winter precipitation. Ensemble mean wet-day frequencies and the distribution of wet and dry period durations remain basically unchanged within the ESSENCE ensemble (used in chapter 4). Although the variability seems to remain rather constant for the ESSENCE ensemble, this may not be true for other climate models. Therefore, one of the major limitations of the delta change technique is that changes in variability cannot be captured. There is no guarantee that the constructed future time series have an appropriate variability, meaning that the sequences of events could change in the future and, for example, more long dry periods could occur. Changes in variability can only be captured by realistic modelling of atmospheric physics which is done by a RCM. Hence, the delta change approach is not a substitute for dynamical downscaling but can be used for quick assessments or studies with limited resources. In addition, it can be used to increase the uncertainty range of a RCM ensemble by post-processing a large ensemble of GCMs.

*Key finding 6:* The top-down approach (from global change to local impact) is useful for assessing uncertainties of changes in flood risk. To address the information needs of local water managers, a bottom-up approach, starting at the local situation, or combined approach is recommended.

The top-down approach has been applied primarily in this thesis; the focus in chapter 3, 4 and 5 has been on assessing the modelling chain from global projections to local impacts. For flood risk management, there is a clear value of this approach. The results of the studies in this thesis give a broad overview of the range of uncertainties for changes in flood risk and the associated damage in the Rhine basin, as projected by the climate models.

The top-down approach does not take into account information about the local context or any social and institutional factors, as also argued in chapter 2. For water managers, this local context is important as it defines how decisions about adaptation strategies can be made and whether the risks are relevant to the decision context (Berkhout et al., 2013). To address the needs of water managers, bottom-up or combined top-down/bottom-up approaches are recommended in other studies (Berkhout, et al., 2013; Dessai & Van der Sluis, 2007; Kwadijk, et al., 2010; Mastrandrea, Heller, Root, & Schneider, 2010; Van Pelt & Swart, 2011). Also, bottom-up approaches can reduce the wide range of uncertainty, which presents the water managers with difficult choices (Brown, Ghile, Laverty, & Li, 2012), by concentrating on the occurrence of conditions that have a major impact on the system and fit the decision context.

The study of Ekström et al. (2013) is one of the few practical examples where the theoretical combination of both approaches has been applied in practice. Therefore, a combined top-down, bottom-up approach was presented in chapter 6, using the simulation game ‘Sustainable Delta’. The climate scenarios and discharge time series that were used in the game, were developed using a top-down approach, from global climate projections to (local) discharge time series. A bottom-up oriented approach was applied for the processing of this information. The experimental group in the workshops assessed the vulnerability of a small stretch of a hypothetical river basin to current climate variability for different indicators such as floods, drought and economy. Then, they decided which of these indicators were important for them and which vulnerabilities should be decreased. In the second phase the water managers of the experimental group assessed future climate variability, which included human induced climate change. Throughout the workshop the water managers learned about the different types of uncertainties and based on this information they assessed which type was important for their decisions on different time scales. The advantage of using this combined approach was that it gave an overview of possible climate changes, but also addressed the local context of the water managers, by the assessment of the vulnerability of the hypothetical river basin and the focus on the relevant uncertainties for the decision context. Although a full bottom-up approach would include more relevant factors (such as politics and governance structures) the game showed that even a simplified example of a combination of bottom-up and top-down approaches can address the information needs of a water manager.

*To summarise the findings of research question 2:* large climate model ensembles should be used to analyse the uncertainty space for changes in flood risk. Although, not capturing the full range of uncertainty, the models give an indication of the uncertainty range. The results can be used to test the sensitivity of a system to changing conditions. Two approaches have been presented that allow for a relatively simple assessment of large climate model ensembles: the delta change approach and the probabilistic framework. These approaches are both top-down driven, which allows for a broad assessment of climate changes and associated impacts for the Rhine basin. It shows what risks can be expected and give an idea of the extent of the risk. For water managers the local context is of importance because it comprises social and institutional factors which are not included in the top-down approach. Bottom-up or mixed approaches can be used to address the needs of the water managers and to assess the vulnerability of both the social and physical system. The 'Sustainable Delta' game was used as an example of the mixed approach; the game allowed the participants to assess the vulnerability of a system within a local context.

*Q3: What is the role of simulation games in the communication of climate change uncertainties between scientists and water managers?*



> *Key finding 7:* Simulation gaming potentially changes the perception of water managers on climate change uncertainty.

Long term climate change uncertainties are perceived as a barrier to adaptation by decision makers (Biesbroek, Klostermann, Termeer, & Kabat, 2013). The findings of research question 1 showed, however, that a large part of the modelling uncertainty for long term changes in (extreme) precipitation and discharge over the Rhine basin can be explained by natural climate variability. As argued in chapter 6, water managers already have considerable experience in dealing with uncertainties associated to the natural variability of the climate system. For the understanding of climate change uncertainties and in decisions involving such information there has been much more attention for the analytical processing than for the role of experiential processes (Marx et al., 2007). Connecting to the experience of water managers can, however, help in the communication of uncertainties (Marx, et al., 2007; Shackley & Deanwood, 2002). Simulation gaming is an instrument that can connect to the experience of water managers and in addition gaming has the potential to stimulate learning (Haug, et al., 2011; Wenzler & Chartier, 1999). Therefore, the simulation game 'Sustainable Delta' was used to communicate about the role of natural climate variability.

To assess the learning potential in the communication of uncertainties an experiment was designed in which a control and an experimental group were given different assignments. The participants' perception about the contribution of natural climate variability relative to human induced change was measured with an ex ante ex post survey. It was hypothesized that the experimental group would perceive the uncertainty of human induced change to be smaller after the experiment. Half of the water managers in the experimental group confirmed this hypothesis, while only 10 % of the control group showed the same result. The results were, however, not significant, which could be due to the small sample size. In conclusion, there is a need to stimulate learning about climate change uncertainties. Our findings show that the game can have a positive effect on learning, but to conclusively say to whether the game influenced perception a larger number of observations would be required.

*Key finding 8*: A simulation game proves to be a useful instrument for the discussion of climate change uncertainties with water managers

In Figure 7.2 (similar to Figure 1.2) two models of science-policy interaction are shown. The first model (a) is the classical model where the climate projections developed by climate scientists are delivered to policy and decision makers. These climate projections are surrounded by complex and large uncertainties which the scientists try to capture and describe to allow for informed decision making. If the range of uncertainties presented is very wide or unclear, however, it presents the decision maker with difficult choices. Often climate science does not match the knowledge demand of the decision maker and despite some interaction between science and policy, this model (a) offers limited solutions for the challenges of dealing with uncertainties. Therefore, the second model in Figure 7.2b is proposed. The model uses a boundary object between science and policy so as to communicate about scientific knowledge in ways that connects to the wishes and desires of both scientists and policy makers. The use of intermediaries for the communication of climate science has been advocated by many others (e.g. Lemos & Rood, 2010; Pidgeon & Fischhoff, 2011; Tribbia & Moser, 2008; White, et al., 2010).

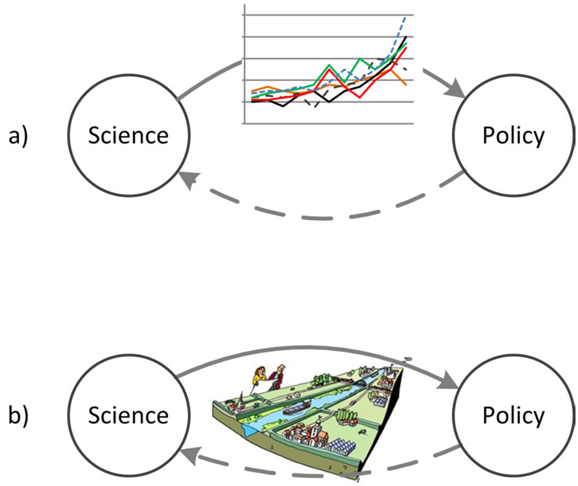


**Figure 7.2.** Two science and policy interaction models. a) Science provides knowledge on uncertainties, which is inherently complex, and policy asks for understandable and usable knowledge. What science delivers in this mode does not connect to the demands of policy. b) Shows the role of a simulation game as boundary object.

The focus of this dissertation was on improving the science to policy communication about the climate uncertainty, which was motivated by the demands of decision makers for usable and understandable science. The findings in chapter 6 show that the game can improve the communication by providing understandable information about climate change uncertainties that connected to their experience. In addition, the simulation game opened up new opportunities for better interaction between science and policy about the climate uncertainties:

First, the water managers were informed in the discussion and by experiencing the game about what can be expected of climate science. During the game, for example, the water managers experienced that on short time scales, the uncertainties of natural climate variability (stochastic uncertainty) are dominant. The two realizations of (only) natural variability showed large differences in the first 30 year, whereas the realization with human induced climate change showed almost no difference with the realization without human induced climate change. It might be easier to discuss the limitations of climate projections when the water managers experience the effects of the different realisations, which in addition possibly creates more transparency.

Second, the experience of the game can decrease the epistemological distance of long term climate change that is created by the large uncertainties about the extent and direction of long term changes. Debates in climate science revolve around how to get decision makers to act pro-active instead of re-active in the face of such long term changes. This issue was also observed in chapter 2, in the evolution of the design discharge for the Rhine in the Netherlands. The simulation game allowed the participants to experience what the impacts of climate change are and what the effects of adaptation measures are in reducing these impacts. The water managers considered this experience very valuable and acknowledged the psychological effect of the game. Playing a simulation game could potentially increase the motivation of decision makers to take adaptation action.

Third, both scientists and water managers are engaged in the discussion of climate change uncertainties during the game and in the debriefing. This provides the opportunity to inform scientists about the needs of water managers and to show water managers where the understanding of uncertainties is still limited. This interaction has been identified by Dilling and Lemos (2011) as one of the main factors that foster usability of climate science in the decision context. For example, during the workshops the water managers highlighted that they had difficulties with the adaptation tipping points approach (Kwadijk, et al., 2010); Which uncertainties are important to take into consideration and when should they prepare to revise their strategy? Scientists might learn that this approach needs more explanation. Moreover, discussing the tipping point approach using the game as a platform could increase the applicability of the approach as water managers can indicate where tipping points would occur from a policy perspective.

*To summarize the findings of research question 3*: the contribution of the simulation game has been analysed by assessing whether the game could be used to influence the perception of the water managers about the uncertainty of natural climate variability for future changes. The results showed that the simulation game has the potential to influence the perception. In addition it is a useful instrument for the communication of climate change uncertainties and the game has the potential to improve the science-policy interaction

## 7.3 Scientific contribution

While detection and attribution of uncertainty have been studied extensively on the global scale for changes in mean temperature and precipitation (e.g. Hawkins & Sutton, 2009; Rosenzweig et al., 2008; Rosenzweig & Neofotis, 2013; Rowell, 2012; Zhang et al., 2007), considerably less work was done for local scale extreme precipitation or coupling with hydrological modelling (although this is a growing body of literature). This thesis presents the first study using a large model ensemble to assess model uncertainty and the role of natural climate variability (i.e. stochastic uncertainty) for changes in extreme precipitation over the Rhine basin. The findings show that for long term changes in mean precipitation epistemic uncertainty dominates, while for changes in extreme precipitation stochastic uncertainty explains the uncertainty range of climate model outcomes.

Two methods have been presented to assess the range of model uncertainty. In chapter 3 the advanced delta change approach was developed further into a method that successfully can be applied to assess changes in mean and extreme precipitation over the Rhine basin. Its main advantage is that it allows for a simple processing of large climate model ensembles, which then can be used for e.g. impact assessments. In chapter 5 the outputs of a large climate model ensemble were used to develop a new framework for the assessment of the probability distribution of flood risk under future climate conditions. Although further research is necessary to refine the method, the results show that such a framework can provide a new (probabilistic) context to discrete scenarios.

In this thesis simulation gaming is recognized as an instrument that can take the role of boundary object and thereby support the communication between science and policy. Up till now, simulation gaming has not been used for the communication of climate change uncertainties. The use of the game was tested in a series of workshops with water managers, who gave positive feedback on the use of this instrument for the communication of science. The work in this thesis has shown that simulation gaming can be used to improve the communication of climate change uncertainties.

The findings of this thesis emphasise the importance of natural variability as source of uncertainty for long term changes in flood risk and present simulation gaming as a novel instrument to communicate about climate change uncertainties, in doing so, support the adaptation to climate change. The main contribution of this study, however, is the connection between two types of research, the technical analysis of different types of climate change uncertainty combined with the communication of the results of this analysis to water managers.

## 7.4 Research limitations and future outlook

This thesis explored the uncertainty space of changes in mean and extreme precipitation over the Rhine basin and the impact of these changes on discharge, using an interdisciplinary approach. In addition, the communication of different types of uncertainties was analysed using a simulation game. Based on this thesis implications for future research are addressed:



In chapter 3 the differences between a RCM and GCM ensemble were shown. Notably, although a GCM determines the boundary conditions of the RCM, the differences between the output of the GCM and the RCM for changes in extreme precipitation were large, but not systematic. It could be interesting to study this further. Why are these differences so large? What physical processes contribute to this difference and what can we learn from this? And do most RCM-GCM combinations show these large differences, or is it only a few combinations that do not match well? Getting more insight in these processes would also improve the knowledge about the uncertainty of dynamical downscaling.

The contribution of natural climate variability was studied in chapter 4. The study was limited by the use of only one initial condition ensemble. It would be interesting to repeat the study using more initial conditions ensembles, which are now available through the CMIP5 archive. It is likely that the internal variability of other models differ from the ECHAM5 model. The output of the model ensembles in this archive would also allow for the use of longer future time periods, which would reduce the sample variability.

The study of chapter 6 used a simulation game for the communication of uncertainties. Up to now, there is not much known about which channel of communication is suitable for which situation, therefore, it would be valuable to make a comparison with other channels of communication, like for example, literature, presentations or other visualisation techniques.

The concept of the study of chapter 6 was based on relating the communication on climate change uncertainties to experience. There are a few other studies on this subject, for example Spence et al. (2011) who related the willingness of saving energy to flood experience. Our findings warrant future research on this subject. Large policy shifts are often re-active, for example, major floods often trigger policy changes (see also chapter 2). For the development of climate adaptation of mitigation strategies, re-active behaviour should be transformed into pro-active behaviour. Relating the possibilities of future events to experience of historic events, including the use of analogies, such as changing frequency of a historical climate extreme e.g. Stott et al. (2004), could potentially help to trigger this pro-active behaviour.

This study has presented new insight on climate change uncertainties and the communication on these uncertainties to water managers. This approach was rather one directional, from science to policy, and did not include an assessment of the policy to science interactions. For the purpose of this study the one directional communication was sufficient, but to learn more about the communication process it is necessary to also involve the decision makers and to learn about their information needs. To this aid, alternative models have been suggested where scientists and decision makers are 'making sense together' (Hoppe, 1999). In the context of climate change 'making sense together' can be about the concept climate change uncertainties or about the ranges of uncertainty that are relevant for the decision context of water manager.

## 7.5 Recommendations for water management

The challenge of being adapted to our current 'stable' climate is that decision makers have to account for average climatic conditions and variable weather conditions, including extremes. In practice, this is not so different from adapting to a changing climate. In both cases water managers have to make judgements about nature, scope and scale of adaptation. In both situations water managers have to question whether it is better to manage every eventuality (in other words extreme events), or accept some level of damage. The difference is that we know less about the probability of eventualities under a changing climate, thereby we do not know what level of risk we are accepting. Adaptation is therefore not always aligned with existing institutions and can challenge existing governance structures. Based on the findings of this thesis three important recommendations for water management are presented below.

1. For flood risk management it is preferable to base an adaptation strategy on large climate model ensembles, not just one estimate.

The emergence of ensemble forecasts can be useful for managing uncertainties in water management. In this thesis ensembles of climate models were presented with ranges of model uncertainty for long term changes in extreme precipitation and discharge over the Rhine basin. Depending on the time scale the uncertainties can be mainly explained by either the difference in climate models or natural climate variability. Water managers can use the presented uncertainty ranges to develop water management plans. Whether these plans are robust against the most extreme changes or just to averages, is a policy choice. Knowledge about the uncertainty space does allow the water managers to explore other choices that increase the robustness against climate change. In the Netherlands, for example, the choice has been made to develop the water protection system to a design discharge of 18,000 $m^3s^{-1}$ for 2100, based on advice of the Second Delta Committee (DeltaCommittee, 2008; Kabat, et al., 2009). The discharge ranges of chapter 4 show that the 1,000 year event could be up to 22,000 $m^3s^{-1}$ at the end of this century. Knowing this, additional plans can be developed to increase the adaptive capacity in case of an extreme event. They could, for example, develop buildings that can withstand floods, and improve evacuation plans, thereby creating multi-layered safety plans. One disclaimer about the use of large ensembles is that they do not sample the full uncertainty space and the value of the output depends on their ability to realistically simulate the climate. Therefore, the outputs should not be seen as predictors for the future, but be used as tools to explore future pathways.

2. Climate change uncertainty should not prevent the development of adaptation strategies.

Uncertainty is an inherent element of research on climate change. The past has learned us that increasing knowledge on climate change has revealed new sources of uncertainty. The results of chapter 6 showed that a large percentage of water managers that joined the workshop believe that uncertainty will be reduced in the future. Even though, the dominant types of uncertainty for long term changes in mean and extreme precipitation are potentially reducible through scientific progress, this should not be used as an argument for inaction. The reduction of uncertainty would only give substantially more confidence of projections of change in discharge at longer time scale, meaning mid-late 21$^{st}$ century, because of considerable uncertainty of natural climate variability related to the human induced climate change signal for the next decade. The results of chapter 6 showed that the participating water managers would prefer to base their strategies on a best estimate, but it is not realistic that this best estimate will become available through science. Some parts of the uncertainty space are not reducible and cannot be quantified, which will always limit the possibility for giving a best estimate. Therefore, the development of adaptation strategies should not hindered by climate change uncertainty, instead the knowledge about climate change uncertainty should be used to test the robustness of adaptation strategies.

3. Experience to deal with climate variability is valuable in the assessment of climate change uncertainties.

Rivers are subject to climate variability and can fluctuate a lot in discharge. Historic descriptions of extreme floods in the Rhine basin shows that discharges higher than 18,000 $m^3s^{-1}$, for example in 1374, could have been reached at Lobith (Herget & Meurs, 2010). This means that within the current climate variability also very high discharges can be reached. The same goes for very low flows. The study of chapter 6 was designed to communicate about the relative role of natural climate variability to human induced climate change. A large part of the differences between projections of climate models for extreme discharges can be attributed to natural climate variability. On short time scales, the signal of human induced climate change can hardly be detected for changes in Rhine river discharge. On longer time scales, the results of this study have shown that natural variability determines a large part of the uncertainty space. The experience of water managers to deal with the uncertainty of natural climate variability can, therefore, be valuable for dealing with an uncertain future.

## 7.6 Epilogue

This epilogue concludes this thesis with a note about the use of the word ‘uncertainty’. In this thesis the word has been used 354 times and there are 325,112 peer-reviewed articles written about the subject, of which 7,295 in relation to climate change (source: SCOPUS). Although I have used the word ‘uncertainty’ consistently through this thesis, I have come to realize over the course of my PhD trajectory that not only uncertainty of science, but also the concept of uncertainty itself can create a barrier between scientists and policy or society. Policy and public communities believe that policy ideally should rest on reliable, robust and hence, robust scientific knowledge

(Shackley & Wynne, 1996) and secure scientific knowledge clarifies and strengthens consensus about appropriate policy response. Therefore, as argued in chapter 6, outside the scientific realm, the notion of uncertainty can have a negative connotation. Scientific uncertainty is often placed on equal footing with flawed science or is interpreted as unsettled science. Uncertainty is where climate science can be most vulnerable (Nisbet and Scheufele 2009). Importantly, the concept of uncertainty serves different roles in the science and policy realms; where uncertainty drives science forward in search for better explanations, it is the same uncertainty that leads policy makers to indecisions. Furthermore, it may challenge the authority of climate scientists (Shackley & Wynne, 1996), because apparently the uncertainty indicates that the scientific knowledge is not yet there where it should be. This problem is also exemplified by the media coverage of global warming, where it is often portrayed as a great diversity among scientists and 'believe' in climate change as if it were a religion. Communicating uncertainty is thus a delicate task that needs to take into account the opposing discourses about the concept. It would therefore be an interesting experiment to compare the response of people to information in which climate science is associated with uncertainty and information in which climate science is associated with another term, for example, likelihood. Likelihood might indicate rather a range of scientific certainty than a range of uncertainty. That being said, I would like to offer my apologies for contributing a large number of 'climate change uncertainties' to the scientific literature.

# Supplementary Information A

## Future changes in extreme precipitation in the Rhine basin based on global and regional climate model simulations (chapter 3)

## A1 Relation between parameters in the transformation formula and extreme-value characteristics

In this appendix we relate the 90% quantile $P_{90}$ and the mean excess to properties of the distribution of seasonal maximum precipitation amounts. In the hydrological literature the Generalized Pareto (GP) distribution has often been used to describe the distribution of the excesses of a high threshold $\mu_0$ (e.g. Beguería (2005); Van Montfort and Witter (1986)):

$$Pr(P - u_0 \le x \mid P > u_0) = \begin{cases} 1 - \left(1 + \frac{\kappa x}{\alpha_0}\right)^{-1/\kappa}, & \kappa \neq 0 \\ 1 - \exp\left(-\frac{x}{\alpha_0}\right), & \kappa = 0 \end{cases} \qquad \text{(A1.1)}$$

where $\alpha_0$ is the scale parameter and $\kappa$ the shape parameter. For $\kappa = 0$ the GP distribution reduces to the exponential distribution. In our application is $P$ the precipitation sum in an arbitrary 5-day interval. A reasonable assumption is that the consecutive 5-day values are independent. The number $K_0$ of exceedances of $\mu_0$ in a given season follows then a Poisson distribution with parameter $\lambda_0$ (the mean number of exceedances) if $\mu_0$ is sufficiently high. For the distribution of the seasonal maximum $P_{max}$ it follows:

$$H(x) = \Pr(P_{max} \le x) = \begin{cases} \exp\left\{-\left[1 + \xi \left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, & \xi \neq 0 \\ \exp\left\{-\exp\left[-\left(\frac{x-\mu}{\sigma}\right)\right]\right\}, & \xi = 0 \end{cases} \qquad \text{(A1.2)}$$

which is a Generalized Extreme Value (GEV) distribution with location parameter $\mu$, scale parameter $\sigma$, and shape parameter $\xi$. The case $\xi = 0$ is known as the Gumbel distribution. The three GEV distribution parameters are uniquely determined by the Poisson parameter $\lambda_0$ and the GP distribution parameters $\alpha_0$ and $\kappa$ (Buishand, 1989;Wang, 1991):

$$\mu = \begin{cases} \mu_0 - \frac{\alpha_0}{\kappa}(1 - \lambda_0^{\kappa}), & \kappa \neq 0 \\ \mu_0 + \alpha_0 \ln(\lambda_0), & \kappa = 0 \end{cases}$$

$$\sigma = \alpha_0 \lambda_0^{\kappa}$$

$$\xi = \kappa \qquad \text{(A1.3)}$$

Note that Eq. (A1.2) only represents the distribution of the seasonal maxima for $P_{max} \ge \mu_0$.

An important property of the GP distribution is that for all thresholds $\mu > \mu_0$, the excesses follow also a GP distribution with the same shape parameter $\kappa$ but with a different scale parameter $\alpha$ (e.g. Wang, 1991; Coles, 2001). The latter is related to the GEV scale parameter $\sigma$ in the same way as $\alpha_0$:

$$\sigma = \alpha\lambda^{\kappa} \tag{A1.4}$$

where $\lambda$ is the mean number of exceedances of $\mu$ in the season of interest. The mean of the excesses is given by (Coles, 2001):

$$\mu_E = \frac{\alpha}{1-\kappa}, \quad \kappa < 1 \tag{A1.5}$$

The GEV scale parameter gives the slope of the extreme-value plot of the seasonal maxima. From Eqs. (A1.4) and (A1.5), it follows:

$$\sigma = \lambda^{\kappa}(1-\kappa)\mu_E, \ \kappa < 1 \tag{A1.6}$$

Hence, the GEV scale parameter is proportional to the mean excess. The constant of proportionality depends on the shape parameter. For $\kappa = 0$, we have $\sigma = \mu_E$. Because $\kappa$ generally does not differ much from zero for 5-day precipitation maxima, the constant of proportionality is close to 1.

If the excesses of the observed 5-day precipitation amounts follow a GP distribution, then the transformation (3.11) changes the scale parameter by a factor $\overline{E}^{F}/\overline{E}^{C}$ and leaves the shape parameter unchanged. The slope of the extreme-value plot changes by the same factor. The transformation does, however, not make explicitly use of an underlying GP distribution. For instance, in the case of a Weibull distribution, it also changes the scale parameter by a factor $\overline{E}^{F}/\overline{E}^{C}$ and leaves the shape parameter unchanged. A different transformation is needed to change the shape of the upper tail of the distribution of $P$. It is, however, difficult to find significant changes in the GP shape parameter.

Assuming independence of the 5-day precipitation sums, the number of exceedances of the 90% quantile $P_{90}$ in a season of $5m$ days follows a binomial distribution with parameters $m$ and $p = 0.10$. The probability that this quantile is not exceeded in a 90-day season is then $0.9^{18} = 0.150$. For a 180-day season this probability equals $0.9^{36} = 0.023$ and thus $P_{90}$ is in the extreme left tail of the distribution of $P_{max}$. The delta method was also tested using the 95% quantile $P_{95}$ instead of $P_{90}$. The changes in the mean excesses of $P_{95}$ turned out to be very sensitive to the method used to estimate $P_{95}$ from the ordered sample of non-overlapping 5-day precipitation amounts owing to the small number of exceedances of this quantile in the short time-series used in this study. This sensitivity can be mitigated by taking all possible, overlapping 5-day precipitation amounts into account for estimating $P_{95}$.

## A2 Weissman approach for extreme values

The 1,000-yr return levels and their changes were estimated from the 15 largest values using the Weissman (1978) approach. Let $X_{1n} \geq X_{2n} \geq \ldots \geq X_{kn}$ be the $k$ largest values in a sample of size $n$ from a distribution $F$. In this study $F$ refers to the distribution of the 10-day maximum basin–average precipitation in the winter half-year.

Under certain conditions on $F$, the joint density of $X_{1n}$, $X_{2n}$, ...$X_{kn}$, can for large $n$ be approximated as (Weissman, 1978):

$$f_{1,\ldots\ldots,k}(x_1, \ldots \ldots, x_k) = \sigma^{-k}\, exp\left[-e^{-(x_k-\mu)/\sigma} - \sum_{i=1}^{k}(x_i - \mu)/\sigma\right] \qquad \text{(A2.1)}$$

where $\mu$ is a location parameter (which depends on $n$) and σ is a scale parameter. Equation (A2.1) applies if, after appropriate scaling, the distribution of the maximum $X_{1n}$ tends to the Gumbel distribution as $n \rightarrow \infty$.

Maximization of the density $f_{1,\ldots,k}$ with respect to $\mu$ and $\sigma$ yields the maximum likelihood estimates:

$$\hat{\sigma} = \bar{X}_{kn} - X_{kn} \qquad \text{(A2.2)}$$

$$\hat{\mu} = X_{kn} + \hat{\sigma} \ln k \qquad \text{(A2.3)}$$

where $\bar{X}_{kn}$ is the average of the $k$ largest values. The $T$-yr return level $x_T$ is then estimated as:

$$\hat{x}_T = X_{kn} + \hat{\sigma} \ln(kT/n) \qquad \text{(A2.4)}$$

In this study $T$ = 1,000, $n$=3,000 and $k$=15. Taking $k$=100 instead of $k$=15 had almost no influence on the bandwidth of the estimated 1,000-yr return levels.

# Supplementary Information B

## Communicating climate (change) uncertainties: simulation games as boundary objects (chapter 6)

## B1 Survey Ex Ante

Document number :

The aim of this survey is to gain insight in the use of climate change scenarios for the development of climate adaptation measures for water management. The survey is anonymous and the results will be processed anonymously, unless you give us explicit permission to do otherwise. We would appreciate it, if you could try answering all questions. We are looking for your opinion and experiences and therefore there are no wrong or right answers. The survey is split up in five parts and contains 19 questions. Answering all the questions of this survey will take about 10 minutes.

### Climate change scenarios

Climate change scenarios are developed to explore the impact of possible changes in the climate. The scenarios are created for various combinations of possible changes in climate variables such as temperature, precipitation, wind and sea level. Examples of climate change scenarios are the IPCC scenarios and the Dutch WB21- and KNMI ’06 scenarios.

1. With which climate change scenarios are you (most) familiar?

……………………………………………………………………………………………………………………………
……………………………………………………………………………………………………………………………

2. In what way are you familiar with these scenarios?

……………………………………………………………………………………………………………………………
……………………………………………………………………………………………………………………………

3. How often do you come into contact with climate change scenarios? This can be by reading about it, discussing them or within your education.
   a. Never
   b. < Once a year
   c. A few times per year
   d Once a month
   e. > Once a month

A few statements are given below. Please indicate for each statement the answer you agree with most.

4. My expectations of climate change are:
   a. Minimal trends; the effect of climate change is less than expected
   b. Maximal trends: the climate will change more drastically than expected
   c. Average trends: the climate will change according to the expectations

d. No opinion

## Climate change uncertainty

5. Could you describe your understanding of the concept 'climate change uncertainty' ?

…………………………………………………………………………………………………………………………

…………………………………………………………………………………………………………………………

A few statements are given below. Please indicate for each statement the answer you agree with most.

6. I expect that, through scientific research, the uncertainty about changes in a future climate will:
   a. Decrease
   b. Remain the same
   c. Increase
   d. Otherwise, namely……………………………………………………………………
   e. No opinion

7. At this moment I think the largest uncertainty in projecting climate change is:
   a. Scenario uncertainty – human behaviour
   b. Model and statistical uncertainty - limited knowledge of our climate and limitations of statistical methods
   c. Climate variability – the climate behaves chaotic and non-linear
   d. Otherwise, namely……………………………………………………………………
   e. No opinion

## Climate Change Adaptation

A few statements are given below. Please indicate for each statement the answer you agree with most.

8. If I would be a water manager I would choose climate adaptation measures that are
   a. Robust against all climate change scenarios
   b. Robust against the most extreme climate change scenario
   c. Robust against the most likely climate change scenario
   d. Otherwise, namely……………………………………………………………………
   e. No opinion

9. If I would be a water managers I think it is necessary for the development of climate adaptation measures to
   a. Calculate the impacts of all climate change scenarios
   b. Calculate the impacts of a few climate change scenarios

c. It is not necessary to calculate impacts of climate change scenarios
d. No opinion

10. Can you explain your answer to question 9?

……………………………………………………………………………………………………………………………

……………………………………………………………………………………………………………………………

11. As a consequence of climate change I think it is necessary to
    a. Take a lot of extra measures in water management
    b. Take a few extra measures in water management
    c. Take no extra measures in water management
    d. Otherwise, namely……………………………………………………………………………
    e. No opinion

12. If I would be a water manager, and I would develop climate adaptation measures, I would start with
    a. Assessing the impact of climate change on the area
    b. Assessing the vulnerabilities of the area
    c. Otherwise, namely……………………………………………………………………………
    d. No opinion

13. Can you indicate on a scale from 1 to 5 to what extent you agree with the statement below?
    "Before I take climate adaptation measures, I want to be certain about the correctness of the projected climate change"
    I do not agree at all is indicated by 1 and I totally agree is indicated by 5.

    1 2 3 4 5 no opinion

14. Some adaptation measures can be taken regardless of uncertainty in projections of climate change because of a low risk of unnecessary social and economic costs. These type of measures are also referred to as 'no-regret' measures.
    Which statement below do you agree most with?
    a. There is a lot of climate change uncertainty and only a few 'no-regret' measures exist
    b. There is little climate change uncertainty and only a few 'no-regret' measures exist
    c. There is a lot of climate change uncertainty and a lot of 'no-regret' measures exist
    d. There is little climate change uncertainty and a lot of 'no-regret' measures exist

## Natural change

Dealing with natural climate changes (climate variability) and the development of measures to deal with river fluctuations has been daily practice for water managers for a long time. For the future, in addition to natural climate changes, water managers could also face climate changes induced by human intervention, like the (increasing) emission of greenhouse gases.

A statement is given below. Please indicate, for this statement, the answer you agree with most.

15. The experience of the 100 years has taught us:
    a. Enough on natural climate changes
    b. Not enough on natural climate changes
    c. No opinion

16. If you were asked to divide uncertainty about the future climate in two components, which percentage of uncertainty would you attribute to natural climate changes and which percentage would you attribute to human induced climate changes?

| | |
|---|---|
| Natural changes | …… % |
| Human induced changes | …… % |
| Total | 100% |

## General

17. Which master or bachelor programme do you follow?

……………………………………………………………………………………………………………………………

18. What is your nationality?

……………………………………………………………………………………………………………………………

19. What is your age?
    a. <20 year
    b. 21-30 year
    c. 31-45 year
    d. 46-60 year
    e. >61 year

20. Do you have any additional remarks in response to this survey?

……………………………………………………………………………………………………………………………
……………………………………………………………………………………………………………………………

Thank you for answering the questions in this survey!

## B2 Survey ex post

Document number :

A few questions of the previous survey are repeated in this survey. The survey is anonymous and the results will be processed anonymously, unless you give explicit permission. We would appreciate it, if you could try answering all questions. We are looking for your opinion, therefore, there are no wrong or right answers. There are 6 questions and answering all the questions of this survey will take about 5 minutes.

### Climate change uncertainty

1. I think the largest climate change uncertainty is:
    a. Human interference
    b. Model and statistical uncertainty
    c. The fact that climate is variable
    d. Otherwise,namely……………………………………………………………………………
    e. No opinion

### Climate Change Adaptation

2. If I would be a water managers I think it is necessary for the development of climate adaptation measures to
    a. Calculate the impacts of all climate change scenarios
    b. Calculate the impacts of a few climate change scenarios
    c. It is not necessary to calculate impacts of climate change scenarios
    d. No opinion

3. As a consequence of climate change, I think it is necessary to
    a. Take a lot of extra measures in water management
    b. Take a few extra measures in water management
    c. Take no extra measures in water management
    d. Otherwise, namely……………………………………………………………………………
    e. No opinion

4. Some adaptation measures can be taken regardless uncertainty in projections of climate change, because of a low risk on unnecessary social en economic costs. This type of measures is also referred to as 'no-regret' measures. Which of the statements below do you agree most with?
    a. There is a lot of climate change uncertainty and only a few 'no-regret' measures exist
    b. There is little climate change uncertainty and only a few 'no-regret' measures exist
    c. There is a lot of climate change uncertainty and a lot of 'no-regret'

measures exist

d. There is little climate change uncertainty and a lot of 'no-regret' measures exist

## Climate Variability

A statement is given below. Please indicate, for this statement, the answer you agree with most.

5. The experience of the 100 years has taught us:
   a. Enough on natural climate changes
   b. Not enough on natural climate changes
   c. No opinion

6. If you were asked to divide uncertainty about the future climate in two components, which percentage of uncertainty would you attribute to natural climate changes and which percentage would you attribute to human induced climate changes?
   Would you change the answers that you gave in the first survey?

| | Previous Answer | Present Answer |
|---|---|---|
| Natural changes | …… % | ……..% |
| Human induced changes | …… % | ……..% |
| Total | 100% | 100% |

If you gave a different answer, can you explain why?

…………………………………………………………………………………………………………………………

…………………………………………………………………………………………………………………………

Thank you for answering the questions in this survey!

## B3 Description of Sustainable Delta game

The participants are given the role of water manager of the Waas delta. The main instruction is to develop a sustainable management plan taking into account the uncertainties about the future. The Waas delta is inspired by a river reach in the Rhine delta of the Netherlands (Haasnoot, et al., 2012). The river and floodplain are highly schematised, but have realistic characteristics. The river is bound by embankments and the floodplain is separated into five dike rings. Little villages, industry, agricultural lands and nature conservation areas surround the floodplain. After an introduction of the Waas system, policy actions and the rules of the game, participants are divided into two teams groups to develop a water management plan. Each team can propose two measures. A limited number of measures can be implemented, either based on the costs or on the number of the measures (e.g. each round 2 measures in total). After negotiation between the teams about the measures, they are then implemented in the simulation model. Next, the model simulates a period of 10 to 30 years (depending on the scenario), and the impacts are discussed. Then, the teams get the opportunity to add or change their measures, and time starts running again. On average four time periods are played in a session, covering a period of 100 years. The session ends with a discussion on what participants experienced, and a translation towards the practice of adaptive water management under uncertain changes.

The simulation model model (for details, see Haasnoot et al. 2012) is implemented in PCRaster (van Deursen 1995) and describes the cause-effect relations within the water system based on results of more complex hydrological and impact models previously applied on the Rhine delta. The model was checked for internal consistency and plausibility of the outcomes by expert judgment. The effects of different transient climate change scenarios are considered through changes in river discharge that cover typically flood and drought situations. The model then calculates the effects on river water levels, probability of dike failure, flood damage, navigability and nature diversity.

Within the model multiple realisations of transient scenarios (time-series) are considered. The transient climate scenarios include three climate scenarios established by the Royal Dutch Meteorological Institute (KNMI): no climate change, G scenario, and Wp scenario (Van den Hurk, et al., 2006). The scenarios are developed using simulations with the KNMI Rainfall Generator (Buishand & Brandsma, 1996). The rainfall generator gives an ensemble of 100 years of precipitation and evaporation data based on the probability of events. With the delta change approach (Lenderink, van Ulden, et al., 2007; Te Linde, 2007) these series were translated into time series for each climate change scenario. The precipitation and evaporation time series for the scenarios were then used in a hydrological model for the Rhine (Te Linde, et al., 2010) to produce discharge data for the Rhine at Lobith, which are the upstream boundary conditions for the simulation model. The discharge time series were made transient by assuming a linear change up to the year 2100. For each of the three climate scenarios, and realisations of precipitation and evaporation events were considered for the next 100 years, resulting in 30 transient climate driver river discharges.

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# Summary

Water managers in the Rhine basin have to take changes, such as population growth, technological changes and climate change, into account. Most of these changes are hard to predict. To assess the vulnerability to climate change, projections are used which are characterized by large uncertainties that stem from different sources. Part of the uncertainty is due to the embedding of human induced change into natural climate variability. In climate science these uncertainties are assessed and quantified but, the quantification is limited by the complexity and nature of the uncertainties. Although the uncertainties are complex, it is important that water managers understand the main uncertainties that are relevant for their decision context. In addition, the managers need to know how to use this knowledge for the development of robust adaptation measures.

The main aim of this thesis is to analyse the climate change uncertainties that are important to take into account for long term water management and to explore the communication of these uncertainties. The study design combines natural and social scientific theories and methods and consists of three different elements: 1) an assessment of the dominant uncertainty for changes in mean and extreme precipitation over the Rhine basin; 2) an assessment of the impact of the main uncertainties on changes in flood risk and associated damage in the Rhine basin and 3) an exploration of the use of simulation gaming to communicate about climate change uncertainties to water managers.

The first part of the thesis (chapter 2,3,4) focusses on changes in mean and extreme precipitation over the Rhine basin between the periods 1961-1995 and 2081-2100. A large ensemble of global climate models (GCMs) was used, post-processed with an advanced delta change approach (see Figure 3.1). Changes were assessed for basin-average 5-day precipitation sums over the winter half-year (October-March), for the mean, 90% quantile and the mean excess, which denotes the amount of precipitation above the 90% quantile. An analysis of variance model was used to study the contribution of stochastic uncertainty (i.e. natural climate variability) to the range of uncertainty as projected by the GCMs for changes in mean and extreme precipitation. The results show that for long term changes in mean precipitation, epistemic uncertainty mainly explains the range of uncertainty, whereas for changes in extreme precipitation, stochastic uncertainty dominates. To derive results for long return periods, 3,000 year resampled time series were used as input for the HBV hydrological model to simulate discharge time series. These series were analysed for long return periods and showed similar contributions of epistemic and stochastic uncertainty as were derived with the analysis of variance model.

In the second part of the thesis (chapter 3,5), different methods to assess the impact of uncertainty on changes in flood risk and associated damage were analysed. First, two different downscaling techniques were compared. The results of GCMs post-processed with the advanced delta change approach were compared to an ensemble of regional climate models (RCMs). The results showed little differences, which validated the use of the advanced delta change approach. Second, a new framework was presented for probabilistic flood risk estimates and associated damage for two case study areas in the Rhine basin. Results indicate considerable changes in flood risk and associated damages. The framework could assist assessments that concern e.g. insurance companies to provide information about future financial risks.

In the third part of the study (chapter 6), the use of simulation gaming to communicate about climate change uncertainties was explored. In particular, the communication about the role of natural climate variability versus the role of human induced change was studied. Several workshops with water managers and students using the simulation game "Sustainable Delta" were organized. During the workshops participants developed an adaptation strategy for a hypothetical river basin. In each workshop, an experimental- and control group were given different assignments. The control group developed an adaptation strategy based on a human induced climate change scenario, whereas the experimental group based their strategy on knowledge of natural climate variability. Although the difference between the groups was not statistically significant, the study showed that simulation gaming facilitates the communication of climate change uncertainties. In addition, the game stimulates the discussion on climate change uncertainties for future water management.

Concluding, the assessment of large climate model ensembles showed that stochastic uncertainty mainly explains the range of uncertainty for long term changes in extreme precipitation as projected by the climate models. Epistemic uncertainty is dominant in explaining the uncertainty range for changes in mean precipitation. Furthermore in addition to dynamical downscaling, the advanced delta change approach is a valid tool to assess the output of climate models for changes in precipitation over the Rhine basin. To communicate about these results to water managers, the findings of this thesis suggest that simulation gaming is a useful instrument

# Samenvatting

Waterbeheerders in het stroomgebied van de Rijn moeten rekening houden met veranderingen in de toekomst zoals populatiegroei, technologische ontwikkelingen en klimaatverandering. Meestal zijn dit soort veranderingen echter moeilijk te voorspellen. Klimaatscenario's worden gebruikt om de kwetsbaarheid met betrekking tot klimaatverandering te onderzoeken. Deze klimaatscenario's worden gekenmerkt door grote onzekerheden, die uit verschillende bronnen ontstaan. Een deel van deze onzekerheid komt, bijvoorbeeld, voort uit het feit dat door mensen verooraakte klimaatverandering is ingebed in natuurlijke klimaatvariabiliteit. In de klimaatwetenschap worden de verschillende types onzekerheden onderzocht en gekwantificeerd, maar dit wordt belemmerd door de complexiteit en de aard van de onzekerheid. Toch is het belangrijk dat waterbeheerders begrijpen welke onzekerheden belangrijk en relevant zijn voor de besluitvorming. Daarnaast is het belangrijk dat de waterbeheerder weten hoe ze deze kennis kunnen gebruiken voor het ontwikkelen van robuuste adaptatiemaatregelen.

Het belangrijkste doel van dit proefschrift is om de onzekerheden op het gebied van klimaatverandering, die belangrijk zijn voor water management op de lange termijn, te analyseren en daarnaast de communicatie van deze onzekerheden te onderzoeken. Deze studie combineert natuurwetenschappelijke- en sociaalwetenschappelijke methodes en theorieën en bestaat uit drie verschillende elementen: 1) een analyse van de belangrijkste onzekerheden voor veranderingen in gemiddelde en extreme neerslag in het stroomgebied van de Rijn; 2) een analyse van het effect van de belangrijkste onzekerheden op veranderingen in overstromingsrisico en bijbehorende schade in het stroomgebied van de Rijn en 3) een verkenning van het gebruik van simulatiespellen bij de communicatie over de onzekerheid van klimaatverandering naar waterbeheerders.

Het eerste gedeelte van dit proefschrift (hoofdstuk 2,3,4) richt zich op veranderingen in gemiddelde en extreme neerslag in het stroomgebied van de Rijn tussen de periodes 1961-1995 en 2081-2100. Een groot ensemble van wereldwijde klimaatmodellen (Global Climate Models – GCMs) werd gebruikt. De variabelen die uit deze modellen komen werden verder bewerkt met een deltamethode (zie figuur 3.1). Veranderingen werden geanalyseerd voor gebiedsgemiddelde 5-daagse neerslagsommen in het winterhalfjaar (Oktober-Maart), het 90% kwantiel en het gemiddelde excess (dit is de hoeveelheid neerslag boven het 90% kwantiel). Een analyse van de variantie (ANOVA) werd gebruikt om de bijdrage van stochastische onzekerheid (natuurlijke variabiliteit) te onderzoeken ten opzichte van de spreiding van onzekerheid zoals gesimuleerd door de GCMs. Dit werd gedaan voor veranderingen in gemiddelde en extreme neerslag. De resultaten laten zien dat epistemische onzekerheid met name de spreiding van onzekerheid verklaart voor veranderingen in gemiddelde neerslag op de lange termijn, terwijl voor veranderingen in extreme neerslag, stochastische onzekerheid dominant is. Geresampelde tijdseries van 3000 jaar werden gebruikt als invoer voor een hydrologische model (HBV). De gesimuleerde afvoerseries die uit het HBV model kwamen werden geanalyseerd voor lange herhalingstijden en lieten dezelfde bijdrages van stochastische en epistemische onzekerheid zien als eerder werden afgeleid uit de analyse van de variantie.

In het tweede gedeelte van dit proefschrift (hoofdstuk 3,5) werden verschillende methodes gebruikt om het effect van onzekerheid op veranderingen in overstromingsrisico en bijbehorende schade te onderzoeken. Ten eerste werden twee verschillende "downscaling" technieken onderzocht. Hiervoor werden de, met de deltamethode bewerkte, resultaten van de GCMs vergeleken met een ensemble van regionale klimaatmodellen (Regional Climate Models- RCMs). De resultaten laten weinig verschillen zien, wat het gebruik van de deltamethode rechtvaardigt. Ten tweede werd een nieuw raamwerk gepresenteerd voor het schatten van overstromingsrisico en bijbehorende schade voor twee gebieden in het stroomgebied van de Rijn. De resultaten laten aanzienlijke veranderingen in overstromingsrisico en bijbehorende schade zien. Het raamwerk kan bruikbaar zijn voor bijvoorbeeld verzekeringsmaatschappijen om informatie over veranderingen in toekomstige financiële risico's te analyseren.

In het derde gedeelte van dit proefschrift (hoofdstuk 6) werd de rol van een simulatiespel bij het communiceren van onzekerheid geanalyseerd. Hierbij werd vooral gekeken naar de communicatie van de rol van natuurlijke klimaatvariabiliteit ten opzichte van door de mens veroorzaakte klimaatverandering. Verschillende workshops met waterbeheerders en studenten werden georganiseerd. Tijdens de workshops werd het spel "Duurzame Delta" gespeeld. In de workshops werd aan de deelnemers gevraagd om een adaptatiestrategie te ontwikkelen voor een hypothetisch rivierengebied. In elke workshop werden verschillende opdrachten gegeven aan een experimentele- en controlegroep. De controlegroep ontwikkelde een adaptatiestrategie op basis van informatie over door de mens veroorzaakte klimaatverandering, terwijl de experimentelegroep een adaptatiestrategie ontwikkelde op basis van informatie over natuurlijke klimaatvariabiliteit. Het gemeten verschil tussen de groepen was niet significant, maar de studie laat wel zien dat een simulatiespel de communicatie over klimaatveranderingonzekerheden kan vergemakkelijken. Daarnaast stimuleerde het simulatiespel de discussie over de rol van klimaatveranderingonzekerheden in toekomstig waterbeheer.

Concluderend, de analyse van een groot ensemble van klimaatmodellen laat zien dat voor veranderingen in extreme neerslag op de lange termijn stochastische onzekerheden voornamelijk de spreiding van onzekerheid verklaart. Epistemische onzekerheid is dominant in het verklaren van de onzekerheid in de spreiding van gemiddelde neerslag. Verder is de deltamethode een waardevolle aanvulling op het gebruik van RCMs om de uitkomsten van klimaatmodellen voor verandering in neerslag over het Rijn stroomgebied te analyseren. Ten slotte laten de bevindingen van dit proefschrift zien dat een simulatiespel een bruikbaar instrument kan zijn om deze resultaten te communiceren naar watermanagers.

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Saskia

# About the author

Saskia van Pelt was born on 15th of April 1984 in Rotterdam. After finishing secondary school in 2002, she studied Environmental System Analysis at Wageningen University. In 2005 she finished her Bachelor and became a full-time member of the board of student association SSR-W. In 2006 she started the master Earth System Science also at Wageningen University. During her internship at ARCADIS she compared climate adaptation measures in both Rotterdam and San Francisco. Also she competed with a team at the Delta Water Award. For her thesis she worked with MeteoConsult on the influence of climate change on the Meuse river. This work resulted in her first peer-reviewed article. She graduated in 2009 and started with her PhD studies at the Earth System Science and Climate Change group and the Forest and Nature Conservation Policy group. For this project she worked with KNMI, Deltares and IVM. The project was funded by KB, Climate changes Spatial Planning and Knowledge for Climate. During her PhD studies she organized the writing week and a PhD trip to Germany.

# List of publications

**Peer-reviewed journal**

Van Pelt, S.C., Haasnoot, M., Arts, B.J.M., Ludwig, F., Swart, R.J., & Biesbroek, G.R.(2013). Communicating climate (change) uncertainties: simulation games as boundary objects. *Environmental Science and Policy*, submitted.

Van Pelt, S. C., Beersma, J. J., Buishand, T.A., Van den Hurk, B. J. J. M., & Schellekens, J. (2013). Uncertainty in the future change of extreme precipitation over the Rhine basin: the role of internal climate variability. *Climate Dynamics*, submitted.

Ward, P.J., van Pelt, S.C., de Keizer, O., Aerts, J.C.J.H., Beersma, J.J., van den Hurk, B.J.J.M., & Te Linde, A.H. (2013). Including climate change projections in probabilistic flood risk assessment. *Journal of Flood Risk Management.* doi: 10.1111/jf3.12029

Van Pelt, S. C., Beersma, J. J., Buishand, T. A., Van den Hurk, B. J. J. M., & Kabat, P. (2012). Future changes in extreme precipitation in the Rhine basin based on global and regional climate model simulations. *Hydrology and Earth System Sciences*, 16, 4517-4530. doi: 10.5194/hess-16-4517-2012, 2012

Van Pelt, S. C., & Swart, R.J. (2011). Climate Change Risk Management in Transnational River Basins: The Rhine. *Water Resources Management*, 25(14), 3837-3861. doi: 10.1007/s11269-011-9891-1

Van Pelt, S. C., Kabat, P., Ter Maat, H. W., Van den Hurk, B. J. J. M., & Weerts, A. H. (2009). Discharge simulations performed with a hydrological model using bias corrected regional climate model input. *Hydrology and Earth System Sciences, 13*(12), 2387-2397. doi: 10.5194/hess-13-2387-2009

**Professional publication**

Van Pelt, S.C., Ward, P.J., Aerts, J.C.J.H., Beersma, J.J.: Nieuwe probabilistische methode om overstromingsrisico's te schatten. *H2O tijdschrift voor watervoorziening en waterbeheer*, 44, 21, p44-46.

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- IPOP Scaling and Governance

**Other PhD Courses**

- Regional Climate Modelling and its use for impact research
- Uncertainty in climate change research: an integrated approach
- Techniques for writing and presenting a scientific paper

**Management and Didactic Skills Training**

- Co-organisation PhD trip to the Max Planck Institute for Biogeochemistry, Jena and PIK - Potsdam Institute for Climate Impact Research (4-8 June 2012)
- Co-organisation CIRCLE workshop Stockholm (2 days) and writing the workshop proceedings
- Co-organisation writing week for ESS-CALM group (5 days)
- Practical supervision of the BSc course "Introduction to Environmental Sciences"

**Oral Presentations**

- *Climate change adaptation in transnational river basins: the Rhine.* IHDP Conference, 2-6 December 2009, Amsterdam, The Netherlands
- *Improving the probability distribution of the change of extreme river flows due to climate change.* SENSE Symposium: Modelling and observing earth system compartments, 22 February 2011, Wageningen, The Netherlands
- *Klimaatdata voor probabilistische scenario's.* Workshop Knooppunt Klimaat, 1 December 2011, Amersfoort, The Netherlands
- *Evaluation of the probability distribution of the future change in extreme precipitation.* EGU General Assembly, 23-27 April 2012, Vienna, Austria
- *Future changes in extreme precipitation in the Rhine basin.* SENSE PhD trip for ESS-CALM and ESA PhD students, at Potsdam Institute for Climate Impact Research , 4-8 July 2012, Potsdam, Germany

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